Multichannel Processing of Broad-Band Multiuser Communication Signals in Shallow Water Acoustic Channels

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***Abstract*— High-throughout multiple-access communication networks are being considered for use in underwater acoustic channels. Bandwidth limitations of underwater acoustic channels require receivers to process broad-band communications signals in the presence of several active users. To deal with the resulting multiple-access interference in addition to high intersymbol interference, spatial variability of ocean multipath is exploited in a multichannel multiuser receiver. Two configurations of such a receiver, a centralized and a decentralized one, are presented in fully adaptive modes of operations. While greatly reducing intersymbol and multiple-access interference, spatial diversity implies high increase in adaptive multiuser receiver complexity. To reduce the complexity of the optimal multichannel combiner, spatial structure of multipath is exploited. The complexity of resulting adaptive decentralized multichannel multiuser receiver is reduced at almost no cost in performance. Comparison of proposed multichannel receivers in an experimental shallow water channel demonstrates superior performance of spatial signal combining. The use of multiple input channels is shown to provide high level of tolerance for the near–far effect in both centralized and decentralized receivers. Decentralized receiver with reduced-complexity combining is found to satisfy the performance/complexity trade-off required for practical receiver realization in shallow water networks.**

I. Introduction

UNDERWATER acoustic (UWA) communications have received much attention in recent years, leading to the development of powerful and reliable receiver algorithms for signal processing in a variety of ocean environments [1], [2]. These algorithms have for the first time demonstrated the possibility of establishing phase-coherent communications in highly variant, dispersive ocean channels. With the feasibility of bandwidth-efficient UWA communications established, the focus of current research is shifting to more demanding communication scenarios, notably to multiuser signal detection as needed in both deep water [3] and shallow water acoustic local area networks (ALAN's) [4].

Limitations to high-speed coherent data transmission in shallow water acoustic telemetry channels include extended, time-varying intersymbol interference (ISI) and large phase fluctuations, both subject to high spatial variability of this channel. To overcome these channel effects, the design of single-user receivers has focused on methods for simultaneous equalization and synchronization. These methods provide a solution to the problem of acquiring a carrier reference needed for coherent demodulation in the presence of multiple signal arrivals of comparable energy. Namely, the single-user receiver structure which has been shown to be effective against the multipath fading in a number of underwater channels, is that of a decision-feedback equalizer (DFE) combined with a digital phase-lock loop (DPLL). In this receiver, described in detail in [1], the equalizer coefficients and the carrier phase estimate are optimized jointly by minimizing the mean-squared error (mse) in the estimated data symbol. The receiver parameters are then adaptively updated using a combination of an RLS algorithm for the equalizer filters and a second-order DPLL for the carrier phase estimate. These adaptive algorithms have been shown to provide the necessary tracking speed for a variety of time-varying underwater channels. The receiver structure initially proposed in [1] was configured to process a single received signal. In [2] it was extended to accommodate spatial diversity processing of many input signals received using an array of sensors. In this multichannel configuration, the single-user receiver accomplishes joint mmse diversity combining, carrier recovery and decision-feedback equalization. Such a receiver was shown to be particularly well suited for application in virtually all of the underwater channels that exhibit extended multipath, such as shallow water channels.

In the network scenario, receiver performance is in addition affected by co-channel, or multiple-access interference (MAI) from other acoustic modems. Since the acoustic bandwidth is severely limited, in order to establish high rate communication between several users, the users must share the same frequency band. In addition, long and variable propagation delay in UWA transmissions precludes the effective use of time-division multiple-access in which each time slot would be dedicated to a single user. These constraints lead to a network scenario in which transmissions from multiple users occur simultaneously in both time and frequency. The performance of such a network strongly depends on the receiver's ability to operate in the presence of strong interference. While in many random-access networks collision of data packets from multiple sources results in the packet loss, multiuser receivers discussed in this paper are designed to resolve collisions between packets, thus increasing the overall throughput of the network.

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A commonly used approach to co-channel signal separation is the use of spread-spectrum signals that provide low cross-correlations among different users. However, due to the limited bandwidth of the UWA channel, the use of large spreading ratios is not feasible without substantially lowering the data throughput. At the same time, severe ISI commonly encountered in shallow water channels makes these channels fundamentally different from many of the radio channels for which the spread-spectrum signals were originally designed. Consequently, when designing the signature waveforms of multiple users, one can either use very low cross-correlations among the waveforms (typical spreading ratios range from three to five) or simply employ a single waveform for all the users. In the latter case, the only distinction among the distorted replicas of different users' signals observed at the receiver remains in the respective channel responses and the underlying data sequences. High cross-correlation among interfering users' signals enhances co-channel interference, contributing to extremely low signal-to-interference ratios (SIR's). In such conditions, a multiuser receiver has to overcome the near-far effect which arises from the difference in the received power levels of the desired and interfering users, caused by varying transmission distances and fading in shallow water channels.

Previous work in the area of multiuser signal detection for underwater communications has asserted the feasibility of coherent reception in the presence of other users, for both mildly distorted vertical transmission channels [3], [5] and severely time-dispersed shallow water channels [4]. This work has focused on single-sensor reception in both centralized and decentralized receiver configurations. By a decentralized station (e.g., a remote node in the network) a receiver is meant which detects signal from a single desired user. Such a receiver has knowledge of the desired user's training sequence only. A centralized receiver (e.g., a base station at the buoy, usually connected to a shore-based central station via a radio link) on the other hand, is a receiver which is capable of detecting the data sequences from all the active users in the network. To achieve simultaneous detection, this receiver has knowledge of all the users' training sequences. For the dispersive shallow water channels it was shown that a single-channel decentralized receiver has performance not only inferior to that of a centralized one, but is also much more sensitive to the level of co-channel interference, failing to perform successfully in the presence of a strong interferer [4]. To overcome this limitation, in this paper we focus on multichannel spatial signal processing for use in shallow water ALAN receivers.

Multichannel, or spatial diversity equalization performs both spatial and temporal signal processing and was shown to be effective in single-user reception for a wide range of range-to-depth ratios in deep and shallow water channels [2]. Spatial signal processing approach offers the most promising way to improve the reception of multiuser signals, by providing not only robustness to fading and reduction in ISI, but also suppression of the multiple-access interference (MAI) [6]. In addition to data detection, the adaptive mode of receiver operation enables the extraction of the fading channel state information, which is utilized by the network router to compute the optimal routes between the acoustic modems in a shallow water ALAN [7]. These results serve as a motivation for developing multichannel, multiuser centralized and decentralized receivers, which are the topic of this paper.

We begin in Section II by considering a system model and the optimal centralized receiver for the detection of multipath-corrupted multiuser signals. A decentralized receiver is obtained as a special case of a centralized one, by restricting the number of output data sequences of the centralized receiver. In an effort to reduce the overall complexity of the receiver, a combining strategy is considered in which the size of the receiver is reduced, but its multichannel processing gain is preserved. In Section III, based on the optimal receiver, fully adaptive realizations suitable for shallow water applications are proposed which incorporate three stages: spatial signal combining, multichannel digital carrier phase recovery, and multichannel decision-feedback equalization. Receiver functions are optimized jointly to ensure minimum mean-squared error performance of data detection. The size of adaptive filters, determined by the length of the ocean multipath and the number of interfering signals, increases with signaling rate and the number of active acoustic modems, ultimately reaching a practical complexity limit, and also limiting the system performance through noise enhancement. To overcome these limitations an efficient design of a decentralized receiver is presented, in which a spatial precombiner is used to reduce the complexity of the multichannel equalizer. Section IV contains experimental results obtained with real data at a one-kilometer range in the Woods Hole harbor off the coast of New England. This site was chosen for preliminary testing of algorithms designed for the real-time ALAN scheduled for deployment in Buzzards Bay. Experimental results demonstrate superior performance of multichannel reception in both centralized and decentralized receiver configurations, requiring no *a priori* knowledge of the channel conditions, spatial distribution of users within the network, or their signature waveforms. Conclusions are summarized in Section V.

II. Optimal Multichannel Reception of Multiuser Signals

In severely dispersive time-varying communication channels, spatial signal processing offers potentials of robustness to fading, reduction of residual ISI and suppression of MAI. However, many different approaches have been used for combining the signals from spatially distributed sensors in the presence of interference. Among the first references to multichannel multiuser signal processing is [8], which analyzes a general case of optimal linear multichannel multiuser reception. A different approach is used in [9], where a structure of decision-feedback interference canceler is imposed on the receiver prior to optimizing its parameters. Multi-input multi-output (MIMO) equalization methods, as applied to the symbol-rate sampled outputs of matched filters in the case of completely known, fixed channels, were summarized in [10]. The multichannel multiuser reception for narrowband signals and nondispersive channel was addressed in [11].

We focus on a general case of multichannel reception of multipath-corrupted multiuser signals which may overlap both in time and frequency. Rather than imposing a certain structure on the receiver, such as that of an interference canceler [9], we begin by addressing the optimal receiver. Such an approach will help to better understand the role of multichannel combining in ISI and MAI suppression, providing a basis for the design of adaptive combiner structures suitable for real-time implementation [12].

A. Channel Model

The communication scenario of interest is illustrated in Fig. 1. From different locations, L users transmit simultaneously to a receiver consisting of a K-element array. The signal of user l, $u_l(t)$, arrives at the receiver over a number of deterministic propagation paths, P_l, each of which is characterized by a complex baseband impulse response $c_{lp}(t)$. The transmitted signal is given in terms of the underlying sequence of data symbols $\{d_l(n)\}$ as

$$u_l(t) = \sum_n d_l(n) p_l(t - nT) \tag{1}$$

where $p_l(t)$ is the basic waveform of user l and T is the common symbol interval. The signal of user l arriving via the pth path is given by a convolution $u_{lp}(t) = u_l(t) * c_{lp}(t)$, and the $P_l \times 1$ vector of such signals is represented as

$$\boldsymbol{u}_l(t) = \sum_n d_l(n) \boldsymbol{g}_l(t - nT) \tag{2}$$

where $\boldsymbol{g}_l(t)$ is the vector of overall (including transmitter and receiver filtering) *path* responses corresponding to user l. The receiver array signal due to user l is given by

$$\boldsymbol{v}_l(t) = \boldsymbol{\Phi}_l \boldsymbol{u}_l(t) \tag{3}$$

where the $K \times P_l$ transformation $\boldsymbol{\Phi}_l$ describes the effects of signal propagation across the array. In the simple case of narrow-band plane-wave propagation, $\boldsymbol{\Phi}_l$ is a matrix with elements $[\boldsymbol{\Phi}_l]_{kp} = \exp(-j(k-l)\varphi_{lp})$, $k = 1, \cdots, K$, $p = 1, \cdots, P_l$, where φ_{lp} is obtained from the angle of arrival θ_{lp} associated with the pth propagation path of user l (see Fig. 1) and the array elements are taken to be equally spaced. The K-element vector,

$$\boldsymbol{f}_l(t) = \boldsymbol{\Phi}_l \boldsymbol{g}_l(t) \tag{4}$$

is the vector of overall channel responses corresponding to user l. The total received signal is now given as

$$\boldsymbol{v}(t) = \sum_{l=1}^{L} \boldsymbol{v}_l(t) + \boldsymbol{\nu}(t) = \overline{\boldsymbol{v}}(t) + \boldsymbol{\nu}(t) \tag{5}$$

where the noise components $\{\nu_k(t)\}$ comprising the vector $\boldsymbol{v}(t)$ are assumed to be independent of the signals. Arranging all the channel responses in a matrix $\boldsymbol{F}(t) = [\boldsymbol{f}_1(t) \cdots \boldsymbol{f}_L(t)]$, and forming a data vector $\boldsymbol{d}(n) = [d_1(n) \cdots d_L(n)]^T$, the received signal is represented as

$$\boldsymbol{v}(t) = \sum_n \boldsymbol{F}(t - nT)\boldsymbol{d}(n) + \boldsymbol{v}(t). \tag{6}$$

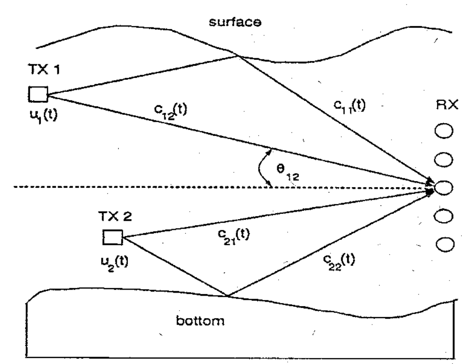


Fig. 1. Propagation model for shallow water channel with receiving array.

This form can be used to represent a signal received over a multipath channel regardless of the existence of any spatial distribution. We therefore retain this general form to obtain the optimal receiver based on joint maximum-likelihood (ML) detection of the data sequence $\{\boldsymbol{d}(n)\}$.

B. Optimal Multichannel Multiuser Receiver

Assuming that the noise is zero-mean, temporally white Gaussian with known covariance $\boldsymbol{R}_\nu$, the log-likelihood function of the data sequence $\boldsymbol{d} = \{\boldsymbol{d}(n)\}$ is given by

$$\Lambda(\boldsymbol{d}) = \int_{T_{\text{obs}}} [\boldsymbol{v}(t) - \overline{\boldsymbol{v}}(t)]' \boldsymbol{R}_\nu^{-1} [\boldsymbol{v}(t) - \overline{\boldsymbol{v}}(t)]\, dt \tag{7}$$

where prime denotes conjugate transpose, and T_{obs} is the observation interval in which the channel responses are assumed to be known. The equivalent function to be maximized with respect to the sequence $\boldsymbol{d}$ can be represented as

$$L(\boldsymbol{d}) = 2\,RE\left\{\sum_n \boldsymbol{d}'(n)\boldsymbol{y}(n)\right\} - \sum_n \sum_m \boldsymbol{d}'(n)\boldsymbol{R}(n-m)\boldsymbol{d}(m) \tag{8}$$

where

$$\boldsymbol{R}(n-m) = \int_{T_{\text{obs}}} \boldsymbol{F}'(t - nT)\boldsymbol{R}_\nu^{-1}\boldsymbol{F}(t - mT)\, dt \tag{9}$$

is the matrix of composite channel cross-correlation functions, and

$$\boldsymbol{y}(n) = \int_{T_{\text{obs}}} \boldsymbol{F}'(t - nT)\boldsymbol{R}_\nu^{-1}\boldsymbol{v}(t)\, dt \tag{10}$$

is the vector of L combiner outputs at time $t = nT$. These expressions imply the optimal receiver structure as given in Fig. 2. Clearly, the combining part of the receiver is separated from the subsequent data-detection part. The optimal combiner for user l, as defined by the expression (10), consists of K channel-matched filters whose outputs are summed and sampled at the signaling rate, as shown in Fig. 3.

The sequence of the optimal combiners' outputs, $\{\boldsymbol{y}(n)\}$, is the only variable of the likelihood function that depends on the input signals, and it thus represents the set of sufficient statistics for determining the most likely transmitted sequence.

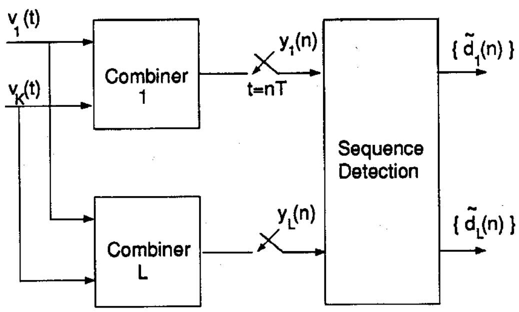


Fig. 2. Structure of the optimal multichannel multiuser receiver.

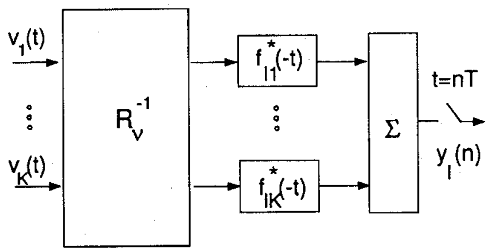


Fig. 3. Optimal multichannel combiner based on channel-matched filtering.

Hence, all the post-combining processing is performed on the L discrete-time signals $y_l(n)$. The optimal post-processor is a ML sequence estimator, which may be implemented using the vector Viterbi algorithm [14]. However, in situations when the channels exhibit long ISI, such as those encountered in many of the UWA channels, the computational complexity of the Viterbi algorithm becomes too high even for the single-user case [1]. The optimal detector is then replaced by some form of equalization. In order to arrive at the optimal equalizer parameters, it suffices to examine the form of its input signal (the discrete-time output of the combiner). This signal is given as

$$\boldsymbol{y}(n) = \sum_m \boldsymbol{R}(n-m)\boldsymbol{d}(m) + \boldsymbol{\eta}(n) \tag{11}$$

where $\boldsymbol{\eta}(n)$ is zero-mean Gaussian with $E\{\boldsymbol{\eta}(n)\boldsymbol{\eta}'(n-m)\} = \boldsymbol{R}(m)$, and $\boldsymbol{R}(m)$ is given in (9). The form of the multichannel multiuser equalizer input signal is completely analogous to that of the single-channel single-user equalizer. This fact makes it possible to deduce the optimal multidimensional equalizer structures simply based on the analogy with the corresponding single-user structures, which are well known and treated in detail in [15]. Assuming independent, unit-variance data symbols, the mmse linear equalizer is represented by a transfer function $\boldsymbol{A}(z) = [\boldsymbol{I} + \boldsymbol{R}(z)]^{-1}$, where $\boldsymbol{R}(z)$ is the z-transform of the sequence $\boldsymbol{R}(m)$. The optimal MIMO linear and decision-feedback equalizers have been presented in [10].

It is important to note that since detection is performed on the sequence of sufficient statistics, optimization of the detector stage can be performed *without altering the optimality* of the front combining part.

C. Reduced-Complexity Multichannel Combining

Although the use of an equalizer eliminates the exponential complexity of the optimal detector, the resulting combiner-equalizer structure may still have complexity prohibitively high for many practical cases. For application in time-varying channels, an adaptive receiver based on the optimal combining of Fig. 3 will be realized as a bank of fractionally spaced adaptive filters. In conditions of severe multipath, such as those observed in the UWA channels whose dispersion may approach the duration of hundred symbol intervals, the complexity of such an adaptive combiner increases dramatically with the number of input channels, limiting a practical number of input channels to only a few. Besides the increase in computational time, a critical disadvantage of large adaptive filters lies in their high noise enhancement, which ultimately limits the gain obtained by increasing the number of input channels. These issues motivate the search for a different combining strategy in which the size of the combiner will be reduced, but multichannel gain preserved.

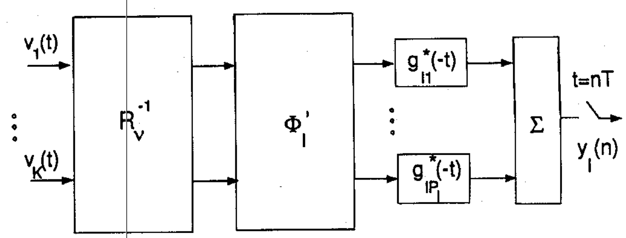


Fig. 4. Optimal multichannel combiner based on path-matched filtering.

So far, we have focused on the optimal receiver which makes no assumptions about the spatial distribution of input signals across the array. Should there exist a certain relationship among the array signals, the optimal combiner gets a special interpretation. If there exists a spatial signal distribution such as that given by (4), the output of the optimal combiner for user l may be represented as

$$y_l(t) = \int_{T_{\mathrm{obs}}} \boldsymbol{g}_l'(t-nT)\boldsymbol{\Phi}_l'\boldsymbol{R}_v^{-1}\boldsymbol{v}(t)\,dt \tag{12}$$

which implies a combiner structure as shown in Fig. 4. This combiner consists of a K-to-P_l spatial precombiner $\boldsymbol{\Phi}_l'$ followed by a bank of path-matched filters. Hence, for a given number of distinct significant propagation paths, of which their are usually only a few, this interpretation of the optimal combiner leads to an adaptive implementation which requires only P_l tapped delay lines per combiner, regardless of the size of the receiving array. It is crucial to note that reduction in complexity of combiners is achieved without altering the optimality of the detection stage, or the overall structure of the optimal receiver which remains as in Fig. 2.

III. Adaptive Multichannel Multiuser Receivers

Although theoretically identical, the two combiner structures give rise to different adaptive implementations, depending on whether knowledge of the spatial signal distribution is available at the receiver. The difference in implementation may lead to significant reduction in complexity without sacrificing the spatial diversity gain. Based on the above discussion we consider adaptive realizations of multichannel multiuser receivers, necessary for the operation in a dynamic underwater

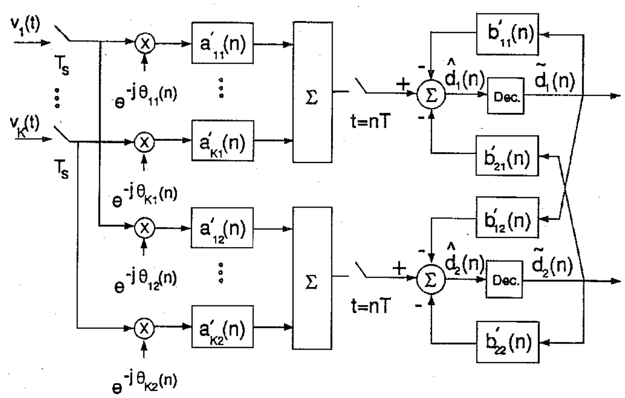


Fig. 5. Centralized multichannel multiuser DFE ($L = 2$).

communication channel. We begin with the general case of a centralized receiver, consisting of a full-complexity multichannel combiner and a multidimensional DFE. The DFE structure is chosen as especially suited for shallow water acoustic channels with long ISI. This receiver structure is more general than the previously developed linear multichannel receiver presented in [8]. A decentralized receiver is obtained from the centralized one by restricting the number of outputs to a single user of interest. The resulting multichannel adaptive mmse receiver is a generalization of the single-sensor adaptive multiuser receiver presented in [16].

A. Full-Complexity Multiuser Receivers

Since no *a priori* knowledge about the exact propagation conditions is available at the centralized receiver, the combiners are realized as banks of adaptive filters. By carefully examining the structures of the MIMO equalizer and the combiners, it is deduced that the linear processing stage of a MIMO DFE can be absorbed into the front, combining part of an adaptive receiver [17]. Thus, only a single bank of adaptive linear FIR transversal filters may be associated with each user in the system.

The complete structure of a fully adaptive receiver is shown in Fig. 5, for the case of two users. In addition to matched filtering, the adaptive filters $\{\boldsymbol{a'}_{k,1}\}$ and $\{\boldsymbol{a'}_{k,2}\}$ accomplish both the functions of linear equalization and MAI suppression. These filters are fractionally spaced (with spacing $T_s \leq$ 1/twice the maximum of all users' bandwidths) and each user's filter bank is accompanied by a K-channel digital phase-lock loop. While this is the most general case for accomplishing the carrier phase tracking separately in each channel/user combination, other configurations are clearly possible. Whether the number of PLL's can be reduced (e.g., one PLL per user) depends on the particular channel.

Assuming that the level of interference (ISI and MAI) is sufficiently reduced at the output of the front section, the feedback section will be able to further reduce the effect of both users' postcursor interference. The direct feedback filters $\boldsymbol{b}'_{1,1}$ and $\boldsymbol{b}'_{2,2}$ are mainly responsible for ISI cancellation, while the cross sections $\boldsymbol{b}'_{1,2}$ and $\boldsymbol{b}'_{2,1}$ deal with MAI cancellation. The role of each of these sections does not depend on the number of input channels, and their design for the single-channel receiver has been studied in [4].

Having established the receiver configuration, the optimal values of its parameters can be determined, assuming that they do not change within the coherence time of the channel. The estimated data symbol of user l at time nT is represented as

$$\hat{d}_l(n) = \sum_{k=1}^{K} \boldsymbol{a}'_{k,l}\boldsymbol{v}_k(n)e^{-j\theta_{k,l}} - \sum_{j=1}^{L} \boldsymbol{b}'_{j,l}\tilde{\boldsymbol{d}}_j(n), \quad l = 1,\cdots,L, \tag{13}$$

where:

- $\boldsymbol{a}'_{k,l}$ is the row vector of filter coefficients corresponding to channel k and user l;
- $\boldsymbol{v}_k(n)$ is the column vector of N T_s-spaced signal samples stored in the feedforward filters at time nT;
- $\theta_{k,l}$ is the carrier phase estimate corresponding to channel k and user l;
- $\boldsymbol{b}'_{j,l}$ is the row vector of coefficients of the feedback filter having j^{th} user's symbol decisions as an input and l^{th} user's interference estimate as an output; and
- $\tilde{\boldsymbol{d}}_j(n)$ is the column vector of M most recent previous symbol decisions obtained for user j at time nt.

In vector notation, the estimated data symbol may be represented as

$$\begin{aligned}\hat{d}_l(n) &= [\boldsymbol{a}'_{1,l}\cdots\boldsymbol{a}'_{K,l} - \boldsymbol{b}'_{1,l}\cdots - \boldsymbol{b}'_{L,l}]\begin{bmatrix}\boldsymbol{v}_1(n)e^{-j\theta_{1,l}}\\ \vdots \\ \boldsymbol{v}_K(n)e^{-j\theta_{K,l}} \\ \tilde{\boldsymbol{d}}_1(n) \\ \vdots \\ \tilde{\boldsymbol{d}}_L(n)\end{bmatrix}\\ &= \boldsymbol{c}'_l\boldsymbol{u}_l(n)\end{aligned} \tag{14}$$

where $\boldsymbol{c}_l$ is the lth user's overall equalizer vector, and $\boldsymbol{u}_l(n)$ is its equivalent input consisting of phase-corrected received signal samples and previously detected data symbols.

The lth user's symbol estimation error, and the corresponding mean-square error (mse) are defined as

$$e_l(n) = d_l(n) - \hat{d}_l(n), \ \mathrm{mse}_l = E\{|e_l^2(n)|\}. \tag{15}$$

The overall mse in simultaneous data detection is the cumulative mse of all users,

$$\mathrm{mse} = \sum_{l=1}^{L} \mathrm{mse}_i. \tag{16}$$

Minimization of the mse with respect to the coefficient vectors $\{\boldsymbol{c}_l\}$ results in their optimal values

$$\boldsymbol{c}_{l_{\mathrm{opt}}} = [E\{\boldsymbol{u}_l(n)\boldsymbol{u}'_l(n)\}]^{-1}E\{\boldsymbol{u}_l(n)d_l^*(n)\}, \qquad l = 1,\cdots,L. \tag{17}$$

The solution for a decentralized system is of the same form, with appropriately redefined input $\boldsymbol{u}_l$ which now contains the desired (lth) user's symbol decisions only. Based on the above optimal solution, a recursive algorithm for time-varying channels will be realized as

$$\boldsymbol{c}_l(n+1) = \boldsymbol{c}_l(n) + \mathrm{RLS}\,[\boldsymbol{u}_l(n),\, e_l(n)], \qquad l = 1, \cdots, L \tag{18}$$

where RLS $[\cdot]$ denotes a one-step recursion of the algorithm chosen from the class of RLS algorithms. The one-step recursion of a least-squares algorithm depends only on the input data vector and the estimation error.

Having defined the update for the combiner/equalizer coefficients, it remains to determine the update for the carrier phases. To do so, it is useful to isolate the factor $\alpha_{k,\,l}$ out of the error e_l, as the only portion dependent on the phase $\theta_{k,\,l}$:

$$\alpha_{k,\,l}(n) = \boldsymbol{a}'_{k,\,l}\boldsymbol{v}_k(n)e^{-j\theta_{k,\,l}}. \tag{19}$$

The phase gradient $\Phi_{k,\,l}$, defined as

$$\frac{\partial\,\mathrm{mse}}{\partial\theta_{k,\,l}} = -2E\{\Phi_{k,\,l}(n)\} \tag{20}$$

is now obtained as

$$\Phi_{k,\,l}(n) = \mathrm{Im}\,\{\alpha_{k,\,l}(n)e_l^*(n)\}. \tag{21}$$

The carrier phase updates are given by

$$\theta_{k,\,l}(n+1) = \theta_{k,\,l}(n) + \mathrm{PLL}\,[\Phi_{k,\,l}(n)], \qquad k = 1, \cdots, K, \quad l = 1, \cdots, L \tag{22}$$

where PLL$[\cdot]$ describes the operation of a digital PLL. A second order loop is preferred for a variety of ocean channels [2].

Hence, the complete algorithms for a multichannel multiuser centralized receiver is given by the expression (18) and (22).

B. Reduced-Complexity Multiuser Receiver

The fundamental bandwidth limitations of the UWA channels necessitate the use of broad-band signals for high-speed communications in which case the full-complexity multichannel processor is the optimal choice. However, its complexity is often too high for a practical implementation, especially in case when a large number of array sensors is available. In this case, a large multichannel processing gain may be obtained; however, if each diversity channel is accompanied by a large adaptive filter, the overall receiver complexity is likely to be unacceptable. To reduce the receiver complexity we may efficiently exploit the form of the optimal combiner based on path-matched filtering which was presented in Section II. Assuming that the number of propagation paths is smaller than the number of input signals, it becomes clear that by implementing the combiner of Fig. 4, a smaller number of adaptive filters will be required than with the structure of Fig. 3. The question remains as to how the combiner parameters will be determined.

If there existed reliable initial information about the spatial signal distribution at the receiver, it could be used to obtain the values of the precombiners. However, such information is unlikely to be available at the receiver, and the approach most beneficial in practice is to conduct *unconstrained* optimization of the combiners and the equalizers, i.e., an optimization in which no *a priori* knowledge about the number of propagation paths or their responses is assumed. In such a way, both the complexity reduction of spatial precombining, and the model-mismatch insensitivity of the full-complexity combiner can be achieved. To preserve performance that matches that of the full-complexity combining in the absence of *a priori* knowledge of the propagation model, the precombiners and the multichannel equalizers need to be optimized jointly. There are many practical advantages of using the reduced-complexity approach, even if it represents a structurally suboptimal solution. A detailed analysis of the principles of reduced-complexity combining as they apply to single-user reception is addressed in [12]. Below, we summarize the algorithm development for the case of a decentralized multiuser receiver, which is the lowest-complexity multiuser receiver structure.

The efficient centralized receiver structure which will utilize adaptive reduced-complexity combining and multidimensional equalization is the subject of the ongoing research. The separation of the spatial and temporal processing precludes a simple merge of the feedforward multidimensional equalizer section with the combining part. However, decentralized receiver structures can fully exploit the benefits of the reduced-complexity combining. The motivation to pursue the complexity reduction of the decentralized structure is further supported by experimental results of Section IV which demonstrate that decentralized reduced-complexity receivers can perform close to the centralized ones at a great reduction in complexity.

The structure of an adaptive decentralized multichannel multiuser receiver which incorporates reduced-complexity combining together with multidimensional DFE receiver is shown in Fig. 6. For notational simplicity we omit the index l and pursue the derivation which holds for any user in the network. An essential part of a practical receiver are the multichannel phase-lock loops (PLL) that enable coherent combining in conditions of severe phase variations. In cases when sufficient coherency between phases can be expected, phase correction can be performed at a point after combining using only P distinct phase estimates, or only a single phase estimate for all the channels. These modifications are easy to carry out, and we concentrate on the case when all K phase estimates are computed. The $K \times P$ precombiner $\boldsymbol{C}(n)$ performs spatial processing only, reducing the number of channels for subsequent P-channel temporal processing and equalization. The receiver parameters to be optimized are given below:

- $\{\theta_k\}$ is the carrier phase estimate of the kth channel,
- $\{\boldsymbol{c}_p\}_{p=1}^P$ are the combiner vectors with K elements $[c_{k,\,p}]_{k=1,\cdots,K}$,
- $\{\boldsymbol{a}_p\}_{p=1}^P$ are the feedforward equalizer vectors with N elements, and
- $\boldsymbol{b}$ is the feedback filter tap-weight vector with M elements.

Tracking of the optimal solution is accomplished through a second-order gradient update for the multichannel PLL and

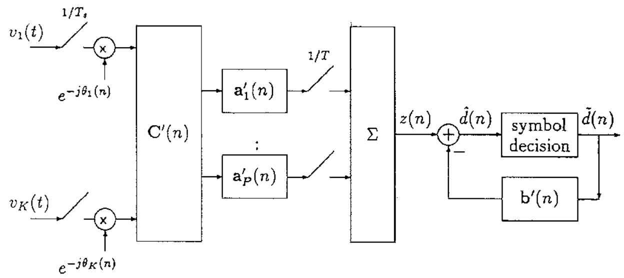


Fig. 6. Decentralized reduced-complexity multichannel DFE.

a double application of the RLS algorithm for obtaining the combiner coefficients and the coefficients of a multichannel DFE. Since the receiver parameters are optimized jointly, the overall adaptation algorithm relies on the single error, $e(n) = d(n) - \hat{d}(n)$.

After compensating for the carrier phase distortions, the input signal samples at time nT are represented in the matrix form

$$\boldsymbol{V}(n) = [\boldsymbol{v}_1(n)e^{-j\theta_1} \cdots \boldsymbol{v}_K(n)e^{-j\theta_K}] \tag{23}$$

where

$$\boldsymbol{v}_k(n) = \begin{bmatrix} v_k(nT + N_1T/2) \\ \vdots \\ v_k(nT - N_2T/2) \end{bmatrix}. \tag{24}$$

The estimated data symbol, which is the input to the decision device, is given by

$$\hat{d}(n) = z(n) - \boldsymbol{b}'\tilde{\boldsymbol{d}}(n) \tag{25}$$

where $z(n)$ represents the output of the linear part of the receiver after coherent combining, and $\tilde{\boldsymbol{d}}(n)$ is the vector of M previously detected symbols stored in the feedback filter.

The variable $z(n)$ at the output of the linear part of the receiver can be represented as

$$z(n) = \sum_{k=1}^{K} A_k(n)e^{-j\theta_k},\ A_k(n) = \sum_{p=1}^{P} c_{k,\,p}^{*}\boldsymbol{a}_p'\boldsymbol{v}_k(n). \tag{26}$$

Taking the phase gradients, the equivalent PLL detector outputs, derived as

$$\Phi_k(n) = \operatorname{Im}\{A_k(n)e^{-j\theta_k}e^*(n)\}, \qquad k = 1, \cdots, K \tag{27}$$

are used for the second-order carrier phase update equations

$$\theta_k(n+1) = \theta_k(n) + \mathrm{PLL}\,[\Phi_k(n)], \qquad k = 1, \cdots, K. \tag{28}$$

To define the equivalent input data vectors for mmse optimization of the combiner/equalizer parameters, the variable $z(n)$ is represented in two ways

$$z(n) = [\boldsymbol{c}_1' \cdots \boldsymbol{c}_P'] \begin{bmatrix} \boldsymbol{V}^T(n)\boldsymbol{a}_1^* \\ \vdots \\ \boldsymbol{V}^T(n)\boldsymbol{a}_P^* \end{bmatrix} = \boldsymbol{c}'\boldsymbol{u}(n) \tag{29}$$

or

$$z(n) = [\boldsymbol{a}_1' \cdots \boldsymbol{a}_P'] \begin{bmatrix} \boldsymbol{V}(n)\boldsymbol{c}_1^* \\ \vdots \\ \boldsymbol{V}(n)\boldsymbol{c}_P^* \end{bmatrix} = \boldsymbol{a}'\boldsymbol{w}(n). \tag{30}$$

The needed data vectors are consequently defined as:

- $\boldsymbol{u}(n)$, the equivalent input to the combiner; and
- $\boldsymbol{w}(n)$, the equivalent input to the multichannel feedforward equalizer.

An RLS type of algorithm is then used twice, to update:

- the combiner vector $\boldsymbol{c}(n)$, as directed by the input data $\boldsymbol{u}(n)$ and the error $e(n)$; and
- the overall equalizer vector

$$\boldsymbol{h}(n) = \begin{bmatrix} \boldsymbol{a}(n) \\ -\boldsymbol{b}(n) \end{bmatrix} \tag{31}$$

as directed by the composite input data vector

$$\boldsymbol{x}(n) = \begin{bmatrix} \boldsymbol{w}(n) \\ \tilde{\boldsymbol{d}}(n) \end{bmatrix} \tag{32}$$

and the same error signal.

Time-recursive solutions are given by

$$\boldsymbol{c}(n+1) = \boldsymbol{c}(n+1) + \mathrm{RLS}_1[\boldsymbol{u}(n),\, e(n)] \tag{33}$$

and

$$\boldsymbol{h}(n+1) = \boldsymbol{h}(n) + \mathrm{RLS}_2[\boldsymbol{x}(n),\, e(n)]. \tag{34}$$

Since a separate update is used for the combiner and the equalizer, both the type of algorithm and the rate of its convergence can be chosen independently for the two updates. When very long channel responses are to be equalized, the multichannel DFE operates under a fast, numerically stable RLS [18]. On the other hand, the combiner's algorithm can be chosen even as standard RLS when KP is small enough to justify such choice. A choice of slightly different RLS forgetting factors, which allows faster convergence of the combiner, may help improve the convergence rate of the overall algorithm. The details of algorithm operation and performance in single-user UWA channels can be found in [12].

IV. Experimental Results

A. Experiment Description

The experimental site for multiuser system testing was chosen in Woods Hole harbor, where the shallow water channel exhibits long and rapidly varying multipath structure. The experiment was conducted in October 1993, as part of a preliminary test for future deployment of a shallow water ALAN.

Two sources were used, transmitting simultaneously in an asynchronous manner. The users shared a common band around the 15-kHz carrier. The transmitter bandwidth was fully utilized at each user's signaling rate of 2000 symbols per second (sps) with the signature waveforms as shown in Fig. 7. The modulation format was BPSK. The case of double packet collision is of special interest as the most likely type of collision a network is expected to experience.

The two users were separated by 5 m, at a distance of 1 km from the receiver. The transmitters and the receiver were submerged at a depth of 5 m in about 20-m deep

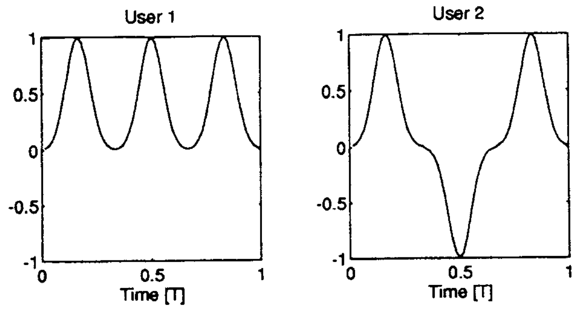


Fig. 7. Signature waveforms in Woods Hole harbor experiment.

water. Directional transducers were employed with 3 dB beamwidths of 60°, while the receiver consisted of a circular array of 16 elements with beamwidths of 120°. Five of the receiving elements facing the transmitters were used for signal processing. The geometry of the experiment with almost no angular resolution between the users precludes the explicit use of beamforming techniques for interference nulling. A situation with network nodes so closely separated can occur when one of the users transmits from a fixed node in the network, while the other user represents a moving source such as underwater vehicle. This situation is the least favorable from the viewpoint of spatial separation of multiple-access channels.

The shallow water channel exhibited multipath spread of about 10 ms, with two to three closely separated significant arrivals followed by long reverberation of lower energy. Such multipath causes ISI to extend over 10-symbol intervals, consequently requiring long feedback filters.

The difference in transmitter powers of the users was 20 dB. Since both users were at the same distance from the receiving array, this different can roughly be considered to be the average near-far ratio observed at the receiver by the weaker user.

B. Performance Results

Despite the strong ISI, relatively high SNR of the stronger user permitted excellent performance, as shown in Fig. 8. This figure illustrates a centralized three-channel receiver performance with respect to the stronger user, designated here as user 1. Shown in the Fig. 8, clockwise from the upper left corner, are the estimated (window-averaged) mse_1, the phases $\{\theta_{k,1}(n)\}$ and the output scatter plot of the estimated data symbols $\hat{d}_1(n)$. After an initial training period, the mse indicates the undisturbed steady-state convergence in the decision-directed mode. Listed in the figure are the receiver parameters: N, M denote the number of taps in each of the feedforward and feedback filters, respectively (fractional spacing of $T_s = T/6$ was used), K is the number of input channels, L is the exponential windowing factor of the RLS algorithm, and $K_{f\,1,2}$ are the phase tracking constants, chosen equal for all the channels. The output SNR of 16 dB is observed, with no detection errors ($P_e \sim 0$) in a data packet of 1500 symbols.

Having a favorable SIR, the stronger user suffers negligibly from the presence of the weaker one, and its performance differs little in a centralized and a decentralized configuration.

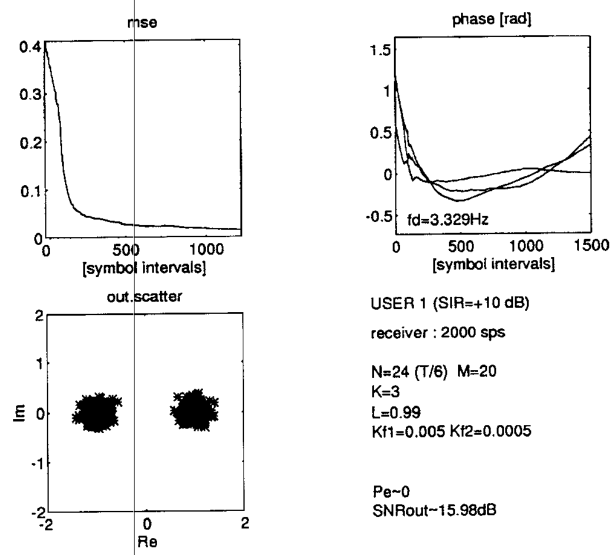


Fig. 8. Performance of a full-complexity centralized receiver for the stronger user.

Contrary to this situation, detection of the weaker user's signal is essentially limited by strong MAI, which is the case of interest for our study. In the experiment, the transmission of the weaker user started after that of the stronger one; thus, both the training and the decision-directed modes of operation took place in the presence of strong MAI. We shall now focus on the weaker user's performance of the centralized and decentralized receivers, comparing the results obtained for a varying number of diversity channels.

In a single-channel configuration, the decentralized receiver performs poorly and, depending on the receiver parameters used and the input channel chosen, may not be able to remain in convergence in the decision-directed mode. However, convergence can be established and performance improved either by using a centralized structure, or by increasing the number of input channels. Fig. 9 shows the performance of a centralized receiver for the weaker user with the same receiver parameters as those of Fig. 8. Centralized reception and multichannel combining provide excellent performance in the low SIR regime. The output SNR in this case is about 2 dB better than that of the corresponding three-channel decentralized receiver, and has performance slightly better than that of a single-channel centralized receiver. Hence, diversity offers not only an improvement with respect to the single-channel case, but provides a decentralized receiver with the capability to achieve the performance of a single-sensor centralized receiver while having no information about the interfering signal.

Fig. 10 summarizes the comparison between centralized and decentralized multichannel multiuser receivers. Shown in this figure is the output SNR as a function of the number of input channels, for centralized and decentralized receiver configurations with two sets of parameters (N, M). All the curves correspond to the weaker user, as indicated by SIR $= -10$ dB.

As expected, both receivers, centralized and decentralized, exhibit improved performance with an increase in the order

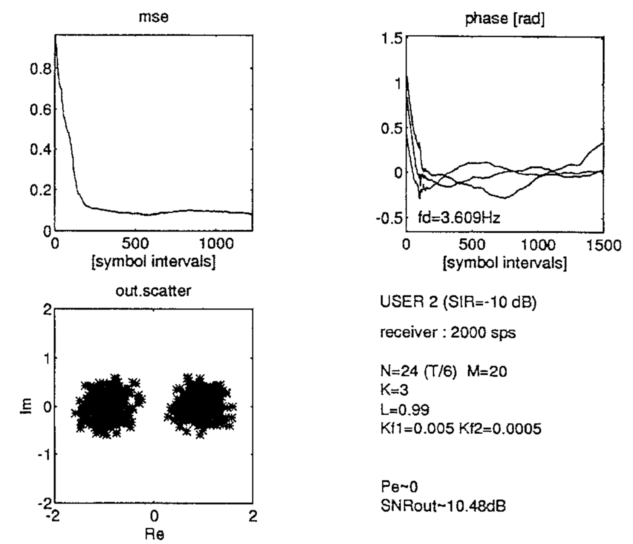


Fig. 9. Performance of a full-complexity centralized receiver for the weaker user.

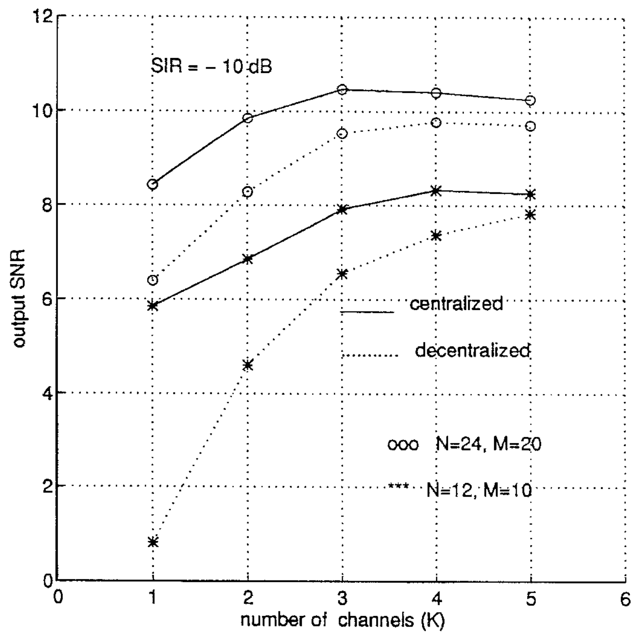


Fig. 10. Performance of the full-complexity, centralized and decentralized receivers for the weaker user as a function of diversity order.

of diversity. However, this effect is more pronounced for a decentralized receiver, notably in the case of smaller filters ($N = 12$, $M = 10$). Such behavior demonstrates the fact that besides ISI, diversity helps to reduce MAI resulting from a strong, unknown interfering signal. At low values of K ($K = 1$, 2), the difference in performance of a centralized and decentralized receiver is striking for the choice of smaller filters. Hence, when only a low order of diversity is available, the use of a centralized receiver represents an effective means for establishing satisfactory performance. However, as the order of diversity increases, the difference in performance between the centralized and the decentralized receiver diminishes, demonstrating the most appealing feature of multichannel processing of multiuser signals: the ability of a decentralized receiver to approach the performance of a centralized one, thus effectively suppressing MAI by exploiting spatial diversity.

At a little cost in performance, the advantages of using a decentralized receiver are twofold. First, knowledge of all the users' training sequences is not required. Second, the complexity of the receiver is lower. Complexity is determined by the size of receiver, since fast algorithms, necessary for applications in severely dispersive channels, have a computational complexity linearly proportional to the total number of adaptively adjusted coefficients. Although advantageous in terms of computational complexity, a decentralized receiver shows higher sensitivity to the choice of receiver parameters than does a centralized one. This fact becomes apparent when the performances obtained with smaller and larger filters are compared: while the performance of the centralized receiver uniformly increases with the receiver size (in the range shown), this is not the case with the decentralized receiver. The decentralized receiver shows more sensitivity to the choice of filter lengths, especially at a low order of diversity. With smaller filters, the decentralized receiver was unable to converge with less than three input channels. Values of N and M too low preclude effective interference suppression, while values too high may result in noise enhancement.

To further reduce the complexity but preserve spatial diversity gain, we resort to the complexity reduction of the decentralized receiver through spatial precombining as discussed in Section III-B. The equalizer vectors are updated using a fast RLS, while the combiner coefficients, of which there are only $K \times P$, allow the use of standard RLS. The choice of the combiner's forgetting factor 0.99 slightly smaller than the equalizers' 0.995, helps to improve the convergence rate of the overall algorithm [12].

Results of reduced-complexity detection are summarized in Fig. 11. The output SNR is shown as a function of the reduced number of channels P which ranges from $P = 1$ to $P = K = 5$. As a reference, the performance curves obtained for the full-complexity $K = P$ channel receivers are provided. Naturally, performance improves as P increases. However, what is interesting to note is that already for $P > 2$, the output SNR reaches a value that remains almost constant with further increase in P. At the same time, reduction in complexity with respect to the full-complexity, five-channel decentralized receiver is significant. The SNR fluctuation accompanying the saturation region is less than 0.3 dB, which is negligible for the receiver performance, so complexity reduction is obtained at almost no cost in decentralized receiver performance.

By exploiting the additional spatial diversity, the reduced-complexity receiver achieves an improvement over the full-complexity P-channel decentralized receiver performance. The corresponding increase in complexity is smaller than if one more channel were added to the full-complexity structure. Another very important feature of the reduced-complexity approach is that it is insensitive to the choice of input channels. It has to be emphasized that the $K = P$ curve for performance of a full-complexity P-channel equalizer is obtained using the best choice of P channels. At $P = 2$ for example, there

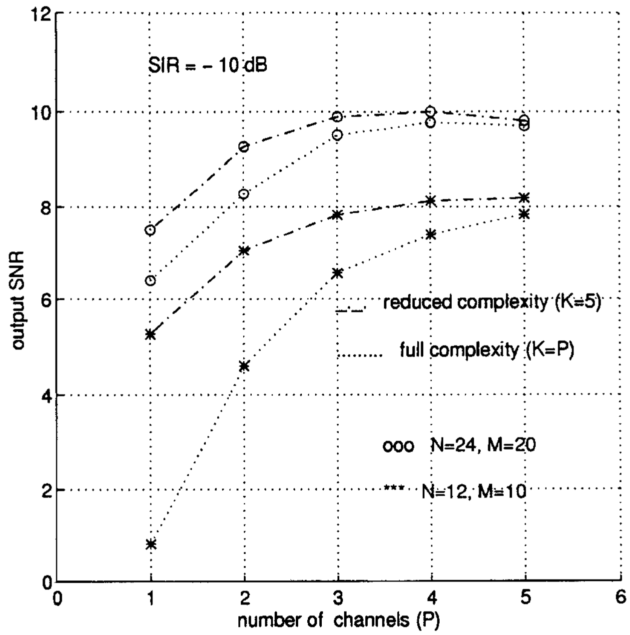


Fig. 11. Performance of a decentralized receiver for the weaker user as a function of the reduced number of equalizer channels P.

was only one choice of the two input channels for which it was possible for the receiver to remain in convergence in the decision-directed mode. On the other hand, the use of a reduced-complexity receiver eliminates this problem. Thus, another important benefit of reduced-complexity decentralized receiver is that while the performance of full-complexity P-channel decentralized receiver strongly depends on the choice of the P input channels, introduction of the $K \times P$ precombiner completely eliminates this dependence. Hence, spatial processing with precombining makes it possible for a decentralized receiver to closely approach the performance of a multichannel centralized receiver while keeping the complexity at minimum.

V. Conclusions

Receivers that are capable of processing broadband signals in the presence of co-channel interference are needed to achieve high throughput network performance in the bandwidth limited UWA channels. Inherently limited by ISI, a multiuser UWA communication system in addition becomes constrained by MAI. Depending on the locations and transmission powers of the multiple users, MAI frequently becomes a dominant factor limiting the system performance.

To improve the quality of existing techniques and provide the desired performance, the use of spatial signal processing in multiuser receivers was investigated. Algorithms were developed for multichannel multiuser systems operating in centralized and decentralized configurations. The receivers presented are based on multichannel combining and optimal, MIMO or scalar DFE, aided by multichannel PLL's. Such a configuration enables efficient exploitation of the spatial variability of the ocean multipath toward reducing the effects of ISI and MAI. In summary, spatial diversity appears to be crucial for robust performance, while at the same time it represents a feasible technique which permits the receiver to be implemented in real time.

Spatial diversity offers additional interference reduction capabilities; however, the usefulness of large broad-band adaptive arrays becomes limited by their computational requirements and noise enhancement. To overcome these problems a class of adaptive combiners, based on purely spatial precombining followed by reduced-complexity multichannel temporal processing was developed.

Performance of the proposed receivers was analyzed in an experimental shallow water network scenario. Results obtained at a SIR as low as -10 dB demonstrate the superior performance of multichannel signal processing in multiple-access UWA communications, in cases of both centralized and decentralized reception. The most prominent feature of the receivers analyzed is their high level of tolerance for the near–far effect, which makes multichannel signal processing a necessity for use in the UWA multiple-access systems. One of the most interesting conclusions of this study is that although a centralized receiver always outperforms the same-complexity decentralized one, spatial signal combining enables a decentralized receiver to achieve performance very close to that of its centralized counterpart. While the complexity of a centralized receiver is significant, the multichannel decentralized receiver is amenable to efficient complexity reduction through spatial precombining, with very little loss in performance.

Experimental results demonstrate the capability of the reduced-complexity decentralized multiuser receiver to provide additional multichannel processing gain, eliminate the spatial dependency of the same-size full-complexity decentralized receiver and approach the performance of the centralized counterpart. The possibility to achieve reduction in complexity at the same time, makes this receiver the choice for the practical realization in the shallow water ALAN.

References

[1] M. Stojanovic, J. Catipovic, and J. Proakis, "Phase coherent digital communications for underwater acoustic channels," *IEEE J. Oceanic Eng.*, vol. 19, pp. 100–111, Jan. 1994.

[2] ——, "Adaptive multichannel combining and equalization for underwater acoustic communications," *J. Acoust. Soc. Amer.*, vol. 94, no. 3, pt. 1, pp. 1621–1631, Sept. 1993.

[3] D. Brady and J. Catipovic, "Adaptive multiuser detection for underwater acoustical channels," *IEEE J. Oceanic Eng.*, vol. 19, pp. 158–165, Apr. 1994.

[4] Z. Zvonar, D. Brady, and J. Catipovic, "Adaptive receivers for interference suppression in shallow water acoustic telemetry channels," to appear in *IEEE J. Oceanic. Eng.*

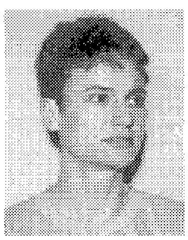
[5] ——, "An adaptive linear multiuser receiver for deep water acoustic local area networks," in *Proc. 1994 Int. Conf. Acoustic, Speech and Signal Processing (ICASSP '94)*, Adelaide, Australia, Apr. 1994, vol. 2, pp. 389–392.

[6] D. Falconer *et al.*, "Advances in equalization and diversity for portable wireless systems," *Digital Signal Processing: A Rev. J.*, vol. 3, pp. 148–162, July 1993.

[7] J. Talavage, T. Thiel, and D. Brady, "An efficient store-and-forward protocol for a shallow water acoustic local area network," in *Proc. Oceans '94*, Brest, France, Sept. 1994.

[8] R. Kaye and D. George, "Transmission of multiplexed PAM signals over multiple channels and diversity systems," *IEEE Trans. Commun.*, vol. COM-18, pp. 520–526, Oct. 1970.

[9] P. Monsen, "MMSE equalization of interference on fading diversity channels," *IEEE Trans. Commun.*, vol. COM-32, pp. 5–12, Jan. 1984.
[10] A. Duel-Hallen, "Equalizers for multiple input/output channels and PAM systems with cyclostationary input sequences," *IEEE J. Select. Areas Commun.*, vol. 10, pp. 630–639, Apr. 1992.
[11] S. Miller, "Detection and estimation in multiple-access channels," Ph.D dissertation, Princeton Univ., Princeton, NJ, 1989.
[12] M. Stojanovic, J. Catipovic, and J. Proakis, "Reduced-complexity spatial and temporal processing of underwater acoustic communication signals," *J. Acoust. Soc. Amer.*, vol. 98, no. 2, pt. 1, pp. 961–972, Aug. 1995.
[13] M. Stojanovic and Z. Zvonar, "Adaptive spatial/temporal multiuser receivers for time-varying channels with severe ISI," in *Proc. 28th Annu. Conf. Inform. Sci. Syst.*, Princeton, NJ, Mar. 1994, pp. 127–132.
[14] W. Van Etten, "Maximum likelihood receiver for multiple channel transmission systems," *IEEE Trans. Commun.*, vol. COM-24, pp. 276–283, Feb. 1976.
[15] J. Proakis, *Digital Communications,* New York: McGraw-Hill, 1995.
[16] S. Verdu, "Adaptive multiuser detection," in *Proc. IEEE 3rd Int. Symp. Spread Spectrum Tech. Applicat. (ISSSTA '94),* Oulu, Finland, July 1994, pp. 43–50.
[17] M. Stojanovic, Z. Zvonar, J. Caripovic, and J. Proakis, "Spatial processing of broadband underwater acoustic communication signals in the presence of co-channel interference," in *Proc. OCEANS '94,* Brest, France, Sept. 1994, pp. II-287–291.
[18] D. Slock and T. Kailath, "Numerically stable fast transversal filters for recursive least squares adaptive filtering," *IEEE Trans. Acoust. Speech, Signal Processing,* vol. 39, pp. 92–114, Jan. 1991.



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