Advanced Sonar Processing Techniques for Underwater Acoustic Multi-Input Multi-Output Communications

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1 Abstract

This paper investigates the issue of high-rate, underwater acoustic communication and the potential of multi-input multi-output (MIMO) techniques to achieve that end; further, this paper suggests that implementation of such a system would benefit from sonar array processing techniques such as multichannel combining. In order to justify this assertion, this paper first develops an algorithm for a hybrid array processing, decision feedback equalization (DFE) MIMO receiver. Subsequently, the hybrid receiver is compared against a traditional MIMO-DFE receiver of similar complexity. These simulations demonstrate that the hybrid receiver improves receiver communication performance and attains higher spatial diversity compared to a traditional MIMO-DFE receiver structure.

2 Introduction

With potential applications ranging from military to commercial to scientific, underwater acoustic (UWA) communications continues to be a growing area of interest to many in both the communications as well as sonar fields; however, due to the unique propagating physics of sound waves in water, the development of high-speed reliable digital communications systems has lagged behind the advancements made in terrestrial wireless communications. In short, the problem of the underwater channel is twofold: a fundamental bandwidth limit as well as a propagation speed that is orders of magnitude below that of terrestrial wireless radiation [1] [2]. In order to address these issues, recent focus has been given to spatial diversity techniques that seek to create orthogonal communication channels to improve spectral utilization. This paper focuses primarily on multi-input multi-output (MIMO) spatial diversity, in which a source broadcasts its message simultaneously over multiple channel inputs to a receiver that utilizes multiple channel outputs, each with a statistically independent look at the signal.

Spatial modulation seeks to use multiple, resolvable propagation paths between two arrays to create, in effect, parallel independent spatial channels within the single, physical ocean channel. The benefits are completely analogous to those of increased bandwidth [3]. At high signal-to-noise ratios (SNR), the capacity of the channel theoretically increases linearly with the minimum number of antennas present in the environment ($\min\{N_{\text{transmit}}, N_{\text{receive}}\}$ b/s/Hz per 3 dB increase in SNR). This result assumes that the receiver knows the response of the channel and the system uses coherent signaling [4]. In order to take advantage of the MIMO gain, the data stream must be space-time encoded by emphasizing either increased system capacity for higher data rates or increased diversity for lower error rates. [3]. Assuming uncorrelated propagation paths and an accurate channel estimate, recovery of the N_{transmit} sequences is possible [3].

3 Problem Statement

Numerous variations of the MIMO receiver have been examined in the literature; however, with the availability of arrays of transducers in underwater sonar systems, this paper adopts a different receiver structure through the introduction of widely used sonar processing techniques. By filtering signals within the spatial domain, sonar array processing appears to provide an intuitive solution towards the end of independent spatial communication channels; therefore, in specific applications, spatial array processing may prove, at the least, a desirable companion to, and potentially, an attractive alternative for analogous approaches in the temporal and frequency domains. Underwater acoustic communication scenarios that would benefit from the application of spatial array processing include: first, systems that steer nulls towards entities with which we do not wish to communicate, either for security reasons or to limit co-channel interference; second, systems that utilize the available spatial diversity to maximize the signal-to-interference plus noise ratio (SINR). In theory, the latter scenario would thereby eliminate the need for lengthy (computationally expensive) equalization filters in channels that exhibit significant multipath spread.

4 Combining Approaches

Utilizing multichannel combining algorithms [5] along with decision feedback equalization, this paper focuses on the development of a hybrid receiver with the goal of reducing receiver complexity and channel overhead while improving signal-to-interference plus noise ratios (SINR) at the equalizer output. Figure 1 demonstrates the proposed receiver architecture: rather than multiple receive antennas, the system employs multiple, spatially independent, receive arrays consisting of multiple, spatially correlated, receive elements organized in an arbitrary spatial pattern. Spatial independence simply implies that the signals received at each array are independent of one another; similarly, spatial correlation implies that, within a particular array, the signal consists of a number of multipath arrivals time-shifted across the array [5]. In the narrowband case, where the signal bandwidth is significantly smaller than the inverse of the propagation time across the array, and for sources in the far field of the array, the time-shift reduces to a simple phase offset. This paper utilizes the narrowband assumption to model the propagation of the multiple signal reflections across the receive array.

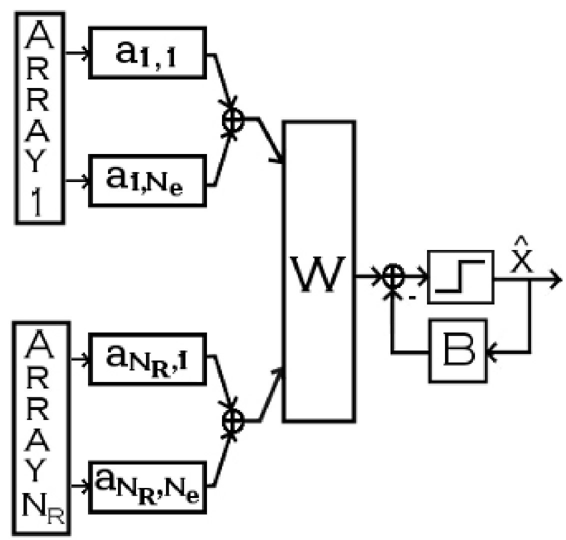


Figure 1: The hybrid multichannel combining and MIMO-DFE receiver developed in Section 4.2. The receiver adopts the following naming convention: combiner gain $a_{j,k}$ and phase $e^{j\phi_{j,k}}$, MIMO-DFE feedforward matrix $\mathbf{W}$, MIMO-DFE feedback matrix $\mathbf{B}$ and symbol decision device, which is represented by a step.

4.1 Channel Model

Let us begin the development of our receiver by first exploring some assumptions about the channel. First, assume that the communication system utilizes N_T transmit sources and let $x_i[n]$ be the discrete-time signal transmitted by source $i \in \{1, \ldots, N_T\}$; further, let us define the $1 \times N_T$ transmit vector $\mathbf{X}^n = (x_1[n] \cdots x_{N_T}[n])^T$. Similarly, assume that the system utilizes N_R receive arrays consisting of N_e array elements and let $y_{j,k}[n]$ be the discrete-time signal received at array $j \in \{1, \ldots, N_R\}$, element $k \in \{1, \ldots, N_e\}$; next, let us denote the $1 \times N_R N_e$ receive vector $\mathbf{Y}^n = (y_{1,1}[n] \cdots y_{N_R,N_e}[n])^T$. Finally, this paper adopts a tapped-delay-line channel model to emulate multiple propagation paths between source and destination.

4.2 Receiver Algorithm

Turning our attention to the receiver depicted in Figure 1, let us begin the development of the multichannel combiner, MIMO-DFE signal processing algorithm. As in [5], this paper adopts multichannel combing as the preferred array processing algorithm towards the end of improved receiver performance. Though suboptimal, the hybrid multichannel combiner, MIMO-DFE receiver demonstrates competitive results and has the benefit of reduced computational complexity. This result depends strongly on the assumption that the signals propagating across the arrays are correlated.

Let us define the output of array j's multichannel combiner as $\hat{y}_j[n] = \sum_{k=1}^{N_e} \tilde{a}_{j,k} y_{j,k}[n]$ where $\tilde{a}_{j,k}$ denotes the complex combiner weight of array j, element k. Again, we can simplify the above equation by packaging the combiner outputs into vector form $\hat{\mathbf{Y}}^n = (\hat{y}_1[n] \cdots \hat{y}_{N_R}[n])^T$ giving $\hat{\mathbf{Y}}^n = \mathbf{A}\mathbf{Y}^n$, where $\mathbf{A}$ denotes the $N_R \times N_R N_e$ matrix of combiner weights.

After multichannel combining, the receiver reduces to the well-studied MIMO-DFE receiver. Due to the wealth of literature on the topic, this paper forgoes an extensive study of the subject in favor of a brief overview. In essence, we want to design a $N_T \times N_R N_f$ feed-forward filter $\mathbf{W}$ as well as a $N_T \times N_T N_b$ feedback filter $\mathbf{B}$ to minimize the mean-squared error between the output sequence $\hat{\mathbf{X}}^n$ and transmitted signal $\mathbf{X}^n$. With a slight abuse in notation, the output of the MIMO-DFE can be written

$$\hat{\mathbf{X}}^n = \mathbf{W}\mathbf{A}\mathbf{Y}^n - \mathbf{B}\hat{\mathbf{X}}^{n-1} \tag{1}$$

Defining the error at time n as $\mathbf{e}^n = \mathbf{X}^n - \hat{\mathbf{X}}^n$, then the values of $\mathbf{A}$, $\mathbf{W}$ and $\mathbf{B}$ that achieve minimum mean square error must satisfy the orthogonality principle $E\big[\mathbf{e}^n\big(\hat{\mathbf{X}}^n\big)^*\big] = 0$. In order to solve for and adapt the filter coefficients that achieve minimum mean-squared error, this paper explores a widely adopted adaptive algorithm called least-mean-squares (LMS).

4.3 Least Mean Squares

Belonging to the class of stochastic gradient algorithms, least-mean-squares (LMS) is a popular linear adaptive algorithm characterized by fast convergence and low computational complexity [6]. Although competing algorithms such as recursive-least-squares (RLS) offer improved convergence rates, the LMS algorithm requires fewer computational resources than any other. For an N-tap finite impulse response (FIR) filter, LMS requires $O(N)$ multiply-and-accumulate operations per update, compared to $O(N^2)$ for RLS. Techniques such as affine projection, which provides a continuum of implementation complexity between LMS and RLS, as well as several "fast" variations of the RLS algorithm attempt to find a happy medium between computational complexity and convergence; however, the need for such alternatives depends largely on the coherence time of the communication channel in question. In light of the goals outlined in Section 4, this paper cares less about the performance of any one specific adaptive filtering algorithm, and instead, focuses on improving communication performance through effective utilization spatial diversity; therefore, the choice of LMS, for both its implementation simplicity as well as its low computational complexity, suits our needs. Keep in mind that a more complex channel tracking algorithm may make sense when actually implementing the receiver in channels that exhibit significant temporal variation.

The primary difficulty in implementing the LMS algorithm for the multichannel combiner, MIMO-DFE receiver centers around the fact that the multichannel combiner and the DFE feedforward taps are inherently intertwined. Let us denote the output of the DFE feedforward filter as

$$\mathbf{z}[n] = (z_1[n] \cdots z_{N_T}[n])^T \tag{2}$$

where

$$z_i[n] = \sum_{j=1}^{N_R} \sum_{l=0}^{N_f-1} \sum_{k=1}^{N_e} a_{j,k} y_{j,k}[n-l] w_{i,j}[l] \tag{3}$$

Taking the derivative with respect to $a_{j,k}$ gives $\frac{\delta z_i[n]}{\delta a_{j,k}} = \sum_{l=0}^{N_f-1} w_{i,j}[l] y_{j,k}[n-1]$, leading to the LMS update equation

$$a_{j,k}^{n+1} = a_{j,k}^n + \mu \sum_{i=1}^{N_T} e_i[n] \Bigg(\sum_{l=0}^{N_f-1} w_{i,j}^n y_{j,k}[n-1] \Bigg)^* \tag{4}$$

The additional summation term emerges from the mismatch between the dimensionality of the error vector and that of the combiner weights. Rather than adapting to an arbitrary error vector entry, the combiner adapts to the aggregate error.

Modifying the LMS algorithm presented in [7] to account for the multichannel combiner, the adaptive MIMO-DFE update equations take the following form

$$\mathbf{W}^{n+1} = \mathbf{W}^n + \mu \mathbf{e}^n \mathbf{A}^{n+1} \mathbf{Y}^n \tag{5}$$

$$\mathbf{B}^{n+1} = \mathbf{B}^n + \mu \mathbf{e}^n \hat{\mathbf{X}}^{n-1} \tag{6}$$

Note the interdependence of the DFE feedforward filter coefficients W and the multichannel combiner element weights A in the LMS update equations: the adaptation of one parameter directly influences the adaptation of the other. As a result, convergence will require a successful collaboration between the two.

5 Simulation Methodology

The simulation results in Section 5.1 were generated using a 2×2 uncoded MIMO system. Utilizing a simple spatial multiplexing scheme, in which the transmitter partitions the source message into N_T separate data streams, the system seeks diversity simply through spatial reuse. Spatial multiplexing requires the following conditions in order to fully realize the benefits of spatial diversity:

1. Independent transmit data streams
2. Independent signal paths from each of the channel inputs to each of the channel outputs
3. Knowledge of the channel at the receiver

Assuming a uniformly generated random bitstream source, we achieve the first condition by simply dividing the source into N_T separate data streams. The second condition is a central requirement for spatial diversity, and thus, for the purposes of our simulation, we shall assume it holds true. In light of this assumption, we generate our simulation channel using an exponentially distributed delay and Rayleigh distributed complex tap weight. The final condition we achieve through training.

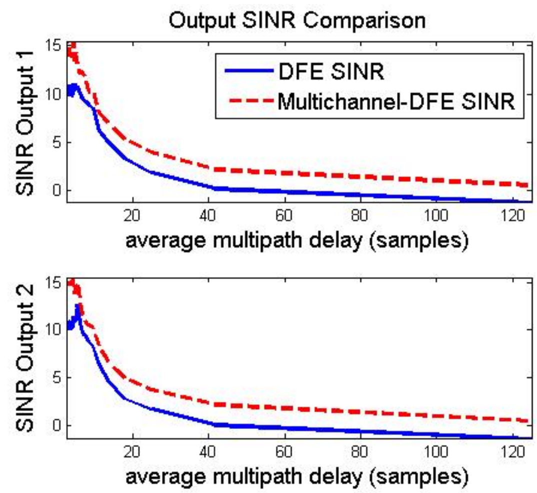
Each receive array has 10 elements, whose spacing satisfy the narrowband assumption. The channel exhibits a total of 20 propagation paths: 5 from each transmit source to each receive array. In terms of computational complexity, the hybrid receiver utilizes 260 adaptive filter elements (20 adaptive combiner weights, 160 DFE feedforward taps and 80 DFE feedback taps) while the traditional MIMO-DFE receiver utilizes 320 adaptive filter elements (200 DFE feedforward taps and 120 DFE feedback taps).

Before continuing, let us briefly explore the validity of the channel model chosen for our simulation set. Though central to both the development and simulation of communication systems, modeling of the underwater acoustic channel continues to be a bone of contention among researchers in the field [8]. Fractured between deterministic ray theory based models and stochastic fading models, no one model effectively characterizes a typical underwater channel. Factors such as depth, distance, temperature, surface agitation and number of scatterers favor certain models over others. For instance, the ray based multipath model used in our simulations has been shown to accurately model the medium range, shallow water channel [8]. Whether this model can be extended to accurately characterize underwater channels of differing ranges and depths exceeds the scope of this paper. Consequently, though we set out to develop a receiver that improves communication performance with the general requirement of spatial diversity, bear in mind that our simulation results are quite specific to one particular underwater channel.

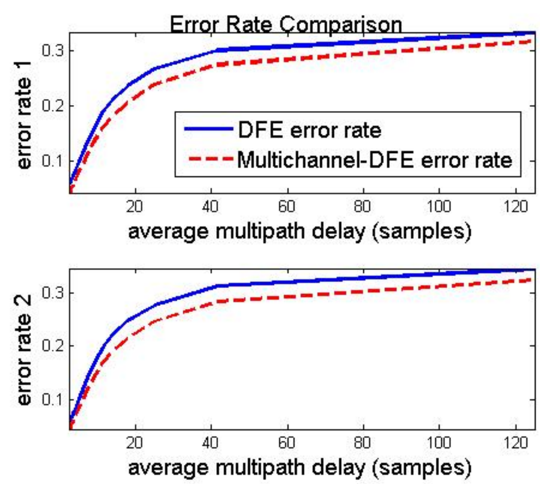
5.1 Simulation Results

The results of the simulation can be seen in Figure 2. Despite similar computational complexity, the hybrid receiver clearly outperformed the traditional MIMO-DFE in both output signal-to-interference plus noise ratios (∼3-5 dB improvement) as well as error rates. Utilizing fewer adaptive filter elements, the hybrid receiver achieved greater spatial diversity utilization than the traditional MIMO-DFE.

Considering the relatively high error rates seen in Figure 2(b), further improvements may be obtained through use of space-time coding, a topic that this paper ignores. In addition, use of sparse equalizers, a common technique employed in UWA communication systems, may alleviate much of the complexity exhibited by the standard DFE benchmarked here within; however, since both receivers compared in this paper utilize the same style of equalizer, it is not clear that sparse equalization would benefit one more than the other. Regardless, this may be an area of potential improvement in terms of both performance as well as reduction in computational complexity, and as such, deserves further exploration.



(a) SINR Comparison



(b) Error Rate Comparison

Figure 2: Simulation results of the 2×2 MIMO system. Improved spatial diversity gain attained with hybrid array receiver proposed in this paper.

6 Concluding Remarks

Exhibiting lower computational complexity and improved receiver performance, the hybrid receiver demonstrates the potential of array processing in compensating for the underwater channel impairments that currently limit achievable acoustic communication capacity. Leveraging the large sonar arrays currently in deployment throughout the world's oceans, the multichannel combiner MIMO-DFE algorithm could greatly improve modern acoustic communication capabilities at the relatively small cost of a software implementation.

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