

Blind Adaptive Sensor-Array Signal Processing for Reliable Underwater Acoustic Communication in Shallow Water

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ABSTRACT

Reliable high data rate wireless communication over the underwater acoustic channel has become more important due to an increasing number of commercial applications. The hostile nature of the transmission medium, however, prohibits mere adaptation of signal processing approaches developed for mobile communication over terrestrial radio-frequency channels. To emphasize these differences, this article starts with a brief description of the properties of underwater acoustic channels and a discussion of their impact on the communication problem. Subsequently, a spatio-temporal receiver architecture that allows for timing estimation, carrier-phase recovery, and intersymbol interference mitigation without explicit training is proposed. To adaptively adjust the equalizer filter coefficients to the actual transmission conditions, the well-known constant modulus algorithm and the newly developed multichannel Shalvi-Weinstein algorithm are introduced and tested with measured data, gathered during the ROBLINKS 1999 experiments.

1.0 INTRODUCTION

For the past decade, there has been a tremendous increase in research and development of underwater acoustic (UWA) communication systems. This has been the response to the growing demand for wireless underwater communications, which was initiated by a shift in applications from almost exclusively military to commercial ones. Examples for such commercial applications of UWA communications are remote control of autonomous underwater vehicles, ocean monitoring, manned and unmanned oceanographic exploration, and communication between submersibles. This development has been accompanied by an ever growing need for higher data rates to cope with the huge amount of data to be transmitted over long distances. Typically, data rates range from a few kilobits per second for simple command and control tasks up to hundreds of kilobits per second for video image transmission [1].

The desired high data rates are in contrast to the transmission conditions induced by the underwater acoustic communication channel, which is bandlimited and highly reverberant, thus posing many obstacles to reliable high-speed digital communication. Therefore, combating the time-varying multipath induced by the transmission channel – especially the technically interesting horizontal shallow-water acoustic communication channel – is considered the most challenging task [16]. While underwater acoustic channels and system share many features with their radio-frequency counterparts, the adverse effects underwater propagation has on the digital acoustic signals often require the development of specialized communication techniques.

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2.0 THE UNDERWATER ACOUSTIC CHANNEL

The underwater acoustic channel is regarded as one of the most difficult communication channels, making special signal processing techniques necessary to ensure reliable high-rate data transmission. A general treatment of underwater sound transmission may be found in the references [3, 19].

2.1 Transmission Loss and Ambient Noise

For a given source level, the signal-to-noise ratio (SNR) at the receiver is influenced by the losses encountered by propagating sound and the ambient noise. The main sources for transmission loss are geometric spreading, absorption, and scattering, with the latter two being strong functions of frequency. Especially attenuation due to absorption rises rapidly with frequency, effectively limiting the maximum operation range of a system or the maximum usable frequency for a given range. Signal detection and reception at the receiver is also affected by various types of noise. There are many sources of ambient noise present in the ocean, with turbulences, ship traffic noise, breaking waves, and rain being the dominant ones. Significant noise can also be generated by marine life such as fish, whales, and shrimp. The ambient noise level decreases with frequency over the operating range of most acoustic communication systems. Therefore, one wants to use as high a centre frequency as possible consistent with transmission loss considerations.

2.2 Multipath Propagation

Multipath propagation occurs whenever there is more than one transmission path between the source and the receiver. In shallow-water, the numerous encountered propagation paths are due to reflections of sound energy at the surface and bottom boundaries. These effects result in multiple versions of the transmitted signal that arrive at the receiving hydrophone, displaced with respect to one another in time and spatial orientation. The delay spread is defined as the time span between the first and the last arrival. Typically encountered delay spreads range from a few milliseconds up to several tens of milliseconds in shallow-water, and even seconds in deep-sea. Such delay spreads translate into several tens, or a hundred of symbol intervals for moderate to high data rates, while typical delay spreads in radio channels are on the order of several symbols only [12]. The reciprocal of the delay spread is an approximate measure of the maximum frequency difference for which signals are still strongly correlated in amplitude. If this so called coherence bandwidth of the channel is greater than the bandwidth of the transmitted signal, the received signal will undergo flat fading: it varies in gain, but the spectrum of the transmitted signal is preserved. If the coherence bandwidth of the channel is smaller than the bandwidth of the transmitted signal, the channel causes frequency selective fading on the received signal. Due to the adverse relationship between the available signal bandwidth and the commonly encountered delay spreads, the technically interesting horizontal underwater acoustic channels are typically frequency selective.

2.3 Doppler Effect

Delay spread and coherence bandwidth describe the slowly time-varying dispersive nature of sound propagation in the ocean. However, they do not offer information about the temporal fluctuations of the acoustic channel caused by source/receiver motion and medium variability. The relative motion between the transmitter and the receiver changes the length of a propagation path. This corresponds to an expansion or compression of the time axis for the received signal, which is referred to as Doppler effect. Since there is a multitude of possible propagation paths, the individual (differential) Doppler effects of each path superimpose at the receiver. When a pure sinusoidal tone is transmitted, it is subject to a mean frequency shift – the Doppler shift – and an additional spectral broadening – the Doppler spread. Typical values for the Doppler spread range from a few Hertz up to several tens of Hertz. The reciprocal of the Doppler spread is a measure of the time interval over which the channel impulse response is invariant. If the reciprocal of the Doppler spread is in the order of the symbol interval, the channel will change during the

transmission of a symbol, thus causing strong distortion at the receiver. In this case, the channel is referred to as fast fading, dominating transmission over the underwater acoustic channel especially for low data rates and a moving source.

3.0 SPATIAL-TEMPORAL RECEIVER ARCHITECTURE

For underwater acoustic channels, the product of delay spread and Doppler spread typically exceeds unity. In this case, the channel is said to be “overspread” [26], while common mobile radio channels are “underspread”. The rapid temporal and spectral fluctuations that come along with an overspread channel prohibit the direct adoption of techniques developed for the mobile radio channel. Special signal processing algorithms are necessary instead, which must be based on space-time processing to allow for reliable, high-speed communication links. Until the early 1990s, it was thought that the rapid variations of the shallow-water channel prevent adaptive signal processing algorithms at the receiver from converging. In their landmark 1994 paper [15], Stojanovic, Catipovic, and Proakis showed that in most cases the channel variations can be decomposed into a slowly varying input delay-spread function, and a fast varying instantaneous phase that is however strongly correlated for different delay taps. Recognizing this fact has led to a suitable receiver architecture for phase-coherent communications.

3.1 Multichannel Digital Receiver

Assume a sensor-array consisting of N_c sensors that are well separated in space. In case of a linear modulation scheme [11], the baseband received signal $r^{(\nu)}(t)$ at sensor ν is given by

$$r^{(\nu)}(t) = \sum_{n=-\infty}^{\infty} a(n) g^{(\nu)}(t - \varepsilon T - nT) e^{j\theta^{(\nu)}(t)} + w^{(\nu)}(t). \quad (1)$$

In Eq. (1), the transmitted symbols $a(n)$, drawn every T seconds from a finite alphabet, are modelled by independent and identically distributed (i.i.d) random variables. The impulse response $g^{(\nu)}(t)$ comprises the effects of the cascade formed by the transmit filter and the possibly slowly varying channel impulse response from the one source to sensor ν . A possible offset between the local clocks at the transmitter and the receiver is denoted by ε , which is assumed to be the same for all sensors for simplicity. The carrier-phase offset $\theta^{(\nu)}(t)$ takes the possible deviation from the nominal carrier frequency into account. Finally, $w^{(\nu)}(t)$ represents additive sensor noise, assumed to be independent from the i.i.d. symbol sequence $a(n)$.

In 1992, Balaban and Salz [2] derived the space-time receiver structure optimal in a minimum mean-squared error (MMSE) sense for the case of known transmission channels from one source to the N_c sensors assuming perfect time and carrier-phase synchronization. It consists of a bank of matched-filters, each matched to the impulse response of the cascade of the common transmit filter and the individual transmission channel from the source to the respective sensor ν , and the additive noise. The signals at the output of the matched-filters are combined into one signal that is subsequently sampled at multiples of the symbol interval T . The discrete-time signal is then equalized with the help of a single transversal filter, possibly of infinite order. Finally, an estimate of the transmitted symbol sequence is obtained at the output of a decision device that utilizes the finite alphabet property of the underlying signal constellation.

To perform its primary task of detecting the transmitted symbol sequence, the receiver must additionally estimate the synchronization parameters (ε , θ) and compensate for their influence on the received signal. Furthermore, the above described receiver architecture implies that all channel impulse responses are known – an assumption not fulfilled in typical communication scenarios. Therefore, an alternative all-digital receiver structure is considered [10], whose multichannel extension is shown in Figure 1.

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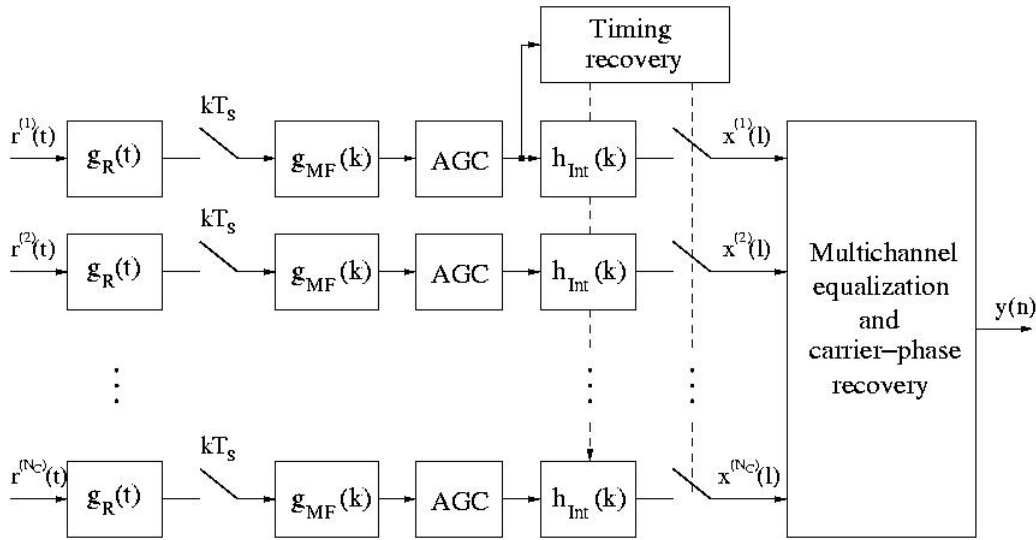


Figure 1: Multichannel receiver front-end, synchronization and equalization

The signals impinging at the sensors 1 to N_c are first converted down to baseband – omitted in Figure 1 – using the nominal carrier frequency and are band-limited using the low-pass filter $g_R(t)$. The band-limited baseband signals are subsequently sampled at multiples of T_s , which is typically a fraction of the symbol interval T . Bandwidth of the low-pass filter and sampling rate $1/T_s$ have to be chosen such that the sampling theorem is fulfilled for the desired signal component contained in $r^{(v)}(t)$ [10]. Instead of individual matched-filters in each subchannel, only the common component matched to the known transmit filter is realized in $g_{MF}(k)$, leaving the remaining channel-dependent part to later processing steps. Prior to further processing, it is however advantageous to adjust the average amplitude dynamics in each subchannel to a common level by using an adaptive gain control (AGC). Then, the normalized offset ε between the timing grids of the transmitter and the receiver is determined and compensated for using digital interpolation techniques characterized by the interpolator $h_{Int}(t)$ and downsampling. A detailed treatment of suitable algorithms for the application at hand is beyond the scope of this contribution and the reader is referred to [9, 10] instead. The outputs of the timing recovery unit are signals $x^{(v)}(l)$ at an intermediate rate $1/T_l$, with $1/T_l = p/T$, p being a natural number. Thus, p represents the temporal oversampling with respect to the symbol duration T . The signals $x^{(v)}(l)$ are input to a processing unit performing joint multichannel equalization and carrier-phase recovery. Possible algorithms for efficient blind space-time adaptive processing that are able to recover the transmitted symbol sequence without explicit training will be treated in detail in the following sections.

3.2 Signal Model

The transmission systems from the source to the input of the N_c intermediate rate sampling units are characterized by impulse responses $h^{(v)}(t)$. The input sequences $x^{(v)}(l)$ to the multichannel equalizer are then given as

$$x^{(v)}(l) = e^{j\theta^{(v)}(lT/p)} \sum_{n=-\infty}^{\infty} a(n) h^{(v)}\left(l\frac{T}{p} - nT\right) + w^{(v)}\left(l\frac{T}{p}\right). \quad (2)$$

Assuming that the physical channels $h^{(v)}(t)$ may be approximated by finite impulse response filters of maximum length of L_h symbol intervals¹ – shorter impulse responses are zero-padded to reach L_h – and that the carrier-phase offset of each subchannel is approximated by a first order polynomial,

$$\theta(t) = \Delta\omega \cdot t + \theta_0^{(v)}, \quad (3)$$

the scalar processes $x^{(v)}(l)$ are jointly cyclostationary with period p [6]. To obtain a wide-sense stationary signal model, the scalar processes are summarized into a vector process

$$\mathbf{x}(n) = e^{jn\Delta\omega T} \boldsymbol{\theta} \sum_{n'=0}^{L_h-1} \mathbf{h}(n') a(n-n') + \mathbf{w}(n), \quad (4)$$

with the (pN_c) -variate vector

$$\mathbf{x}(n) = \left[x_0^{(1)}(n), \dots, x_0^{(N_c)}(n), \dots, x_{p-1}^{(1)}(n), \dots, x_{p-1}^{(N_c)}(n) \right]^T, \quad (5)$$

including the samples of all sensors per symbol interval – $(\cdot)^T$ denotes the transpose operator, the $(pN_c) \times (pN_c)$ dimensional unitary diagonal matrix

$$\boldsymbol{\theta} = \text{diag} \left(e^{j\theta_0^{(1)}}, \dots, e^{j\theta_0^{(N_c)}}, \dots, e^{j((p-1)\Delta\omega T / p + \theta_0^{(1)})}, \dots, e^{j((p-1)\Delta\omega T / p + \theta_0^{(N_c)})} \right), \quad (6)$$

and $\mathbf{h}(n)$ and $\mathbf{w}(n)$ are defined equivalent to Eq. (5). As long as $pN_c > 1$, the same vector model (4) results from oversampling in space ($N_c > 1$) or time ($p > 1$), thus allowing a compact and efficient representation of joint space-time signal processing.

3.3 Multichannel Equalization

According to Figure 1, the N_c intermediate rate sequences $x^{(v)}(l)$ enter a multichannel equalizer, which is composed of a bank of N_c – possibly fractionally-spaced – equalizers. Each filter acts on one sensor output sequence as shown in Figure 2, but typically all filters are jointly optimised to enhance efficiency.

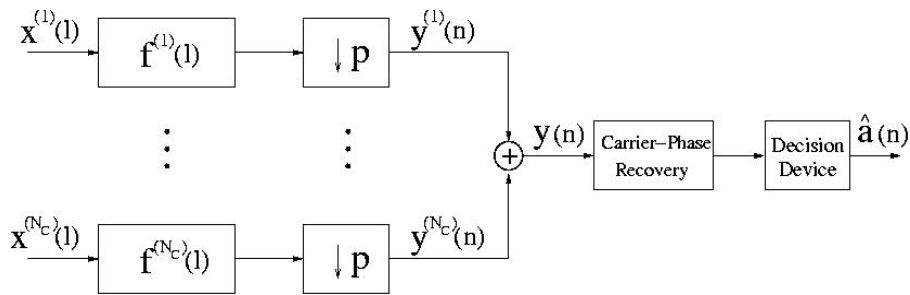


Figure 2: Multichannel equalization and carrier-phase recovery

In order to coherently combine all sequences $y^{(v)}(n)$, a phase-offset compensation has to be performed in all physical subchannels. However, if the phase-offsets show enough correlation, their compensation can

¹ Regarding techniques for estimating the length of the channel impulse response without cooperation by the transmitter, the interested reader is referred to [20] and the references therein.

be performed after subchannel combining [14]. This is also shown in Figure 2. Assuming a common length of L_f symbol intervals for all equalizer filters $f^{(v)}(l)$ and employing a polyphase decomposition of the filters to effectively describe the multirate system, it can be shown [24] that the combined output of the multichannel equalizer may be written as

$$y(n) = \sum_{n'=0}^{L_f-1} \mathbf{f}^T(n') \mathbf{x}(n-n') = \mathbf{f}_{L_f}^T \mathbf{x}_{L_f}(n), \quad (7)$$

with $\mathbf{x}(n)$ given in Eq. (5), the (pN_c) -variate vector $\mathbf{f}(n)$ being constructed correspondingly, and

$$\mathbf{f}_{L_f} = \left[\mathbf{f}^T(0), \dots, \mathbf{f}^T(L_f - 1) \right]^T, \quad (8)$$

$$\mathbf{x}_{L_f}(n) = \left[\mathbf{x}^T(n), \dots, \mathbf{x}^T(n - L_f + 1) \right]^T. \quad (9)$$

The remaining tasks are the proper selection of the equalizer length L_f depending on the estimated channel length L_h [18], and the adaptation of the equalizer filter coefficients and the carrier-phase recovery unit to the transmission conditions in order to recover the transmitted sequence $a(n)$ with minimal probability of error. The conventional approach employs transmitted symbols as a reference, which are also known to the receiver. Although this receiver structure of [15] is canonical nowadays, its major drawback is the large training overhead necessary for adaptation in rapidly time-varying environments. A fundamental problem also arises from new applications like underwater acoustic communication networks, which are in the focus of current research. It is inefficient to re-train all receivers if a new node joins the network or if an existing receiver temporarily loses convergence. Therefore, receiver architectures that allow for efficient blind space-time adaptive processing techniques to equalize communication channels are of current interest. The notion “blind” means that no training symbols periodically inserted into the data stream are used to adjust the receiver to the current channel conditions. This task shall be performed solely based on the received signal and some known (statistical) properties of the transmitted symbol sequence $a(n)$ instead. Suitable algorithms will be the topic of the following sections.

4.0 MULTICHANNEL CONSTANT MODULUS ALGORITHM

The conventional equalization of communication channels employs transmitted symbols as a reference, which are also known to the receiver. The signal at the output of the equalizer is compared with the reference symbols to extract an error signal. The criterion for adaptation of the equalizer filter coefficients is then the minimization of the expected power of this error signal, with the actual minimization step being usually performed recursively using a least mean squares (LMS) algorithm or a recursive least-squares (RLS) algorithm [11]. The first blind equalization algorithms proposed in the literature tried to mimic this approach: the coefficients of the equalizer filter are determined by optimisation of a cost function, which, however, is not derived from an Euclidean measure of distance. For the recursive optimisation of such a generalized cost function, usually an LMS-like stochastic gradient descent (SGD) algorithm is used [5]. The most prominent example from this class of algorithms is the constant modulus algorithm, developed by Treichler and Agee in 1983 [17]. In the following, an extension of their basic algorithm is treated that allows for efficient blind space-time adaptive processing [8].

4.1 The Constant Modulus Criterion

The goal of blind equalization is the design of adaptive algorithms that converge to the optimal zero-forcing (ZF) or MMSE equalizer setting [11] without the assistance of training symbols. A common approach is based on the optimisation of generalized cost functions $J(\mathbf{f}_{L_f})$, which can be written as

$$J(\mathbf{f}_{L_f}) = E\{\psi(y(n))\}, \quad (10)$$

with ψ being a scalar, real-valued function of the signal $y(n)$ at the output of the equalizer and $E\{\cdot\}$ denoting the expectation operator. The cost function should represent the actual amount of intersymbol interference. Thus, minima of $J(\mathbf{f}_{L_f})$ also correspond to minima of the intersymbol interference. In 1980, Godard [7] introduced a class of algorithms that are specified by the cost functions

$$J_G(\mathbf{f}_{L_f}) = E\left\{\frac{1}{q} \left(|y(n)|^q - R_q \right)^2 \right\}, \quad (11)$$

indexed by the positive integer q , where

$$R_q = \frac{E\{|a(n)|^{2q}\}}{E\{|a(n)|^q\}}. \quad (12)$$

The special cost function for $q = 2$ was independently developed by Treichler and Agee [17] as the constant modulus algorithm (CMA) using the philosophy of property restoral. For input signals to the channel that have a constant modulus $|a(n)|^2 = R_2$, the CMA penalizes output samples $y(n)$ that do not have the desired constant modulus characteristics.

To establish a stochastic gradient descent algorithm [5], the gradient of the cost function (11) for the special case $q = 2$ with respect to the equalizer filter coefficients is taken and the expected value is replaced by the current realization. This leads to the recursion

$$\mathbf{f}_{L_f}(n) = \mathbf{f}_{L_f}(n-1) - \mu_f e(n, n-1) \mathbf{x}_{L_f}^*(n) \quad (13)$$

for the filter coefficient. In Eq. (13), the a-priori error signal $e(n, n-1)$ is given by

$$e(n, n-1) = \left(|y(n, n-1)|^2 - R_2 \right) y(n, n-1) \quad (14)$$

with the a-priori signal

$$y(n, n-1) = \mathbf{f}_{L_f}^T(n-1) \mathbf{x}_{L_f}(n), \quad (15)$$

the positive step-size μ_f , and $(\cdot)^*$ denoting complex conjugation. To initialise the recursion, usually a single non-zero value $1/N_C$ is placed close to the middle of the impulse response of each physical subchannel.

It follows from the special form of the cost function (11) for $q = 2$ that the CMA is invariant to a possible carrier-frequency offset $\Delta\omega$. Therefore, the equalizer parameter adaptation can occur independent of the operation of the carrier-phase recovery unit. This results in an already reconstructed signal constellation at the output of the equalizer, which rotates with a frequency $\Delta\omega$ in the complex plane. This rotation can be compensated for by a subsequent decision-directed phase-locked loop as proposed in [7].

4.2 Experimental Results

Within the EC-funded project ROBLINKS, in spring 1999, a sea trial for underwater communication was conducted in the North Sea about 10 km off the Dutch coast. At the transmitting side, an almost omnidirectional acoustic source was deployed from the stern of a support ship and lowered to a depth of approximately 9 m. The total water depth in this shallow-water area is about 18 m. The signals were received by a vertical array consisting of $N_C = 3$ pairs of hydrophones, separated horizontally by 15 cm at depths of approximately 7, 11, and 15 m below the sea surface. The array was fixed to an oceanographic platform, which also hosted all recording facilities. The support ship anchored at various positions with distances of 1, 2, 5, and 10 km from the platform. In addition, the ship was sailing at moderate speed the last two days to obtain measurements with a moving source. More details on the ROBLINKS experiments can be found in [25].

To examine the performance of the described receiver structure, OQPSK-modulated [11] communication data at a rate of 1560.67 bit/s that had been recorded while the ship moored at a distance of 2 km away from the platform was analysed. The carrier frequency was 3079 Hz and approximately 100000 data bits were continuously transmitted. The signals received at three vertically displaced hydrophones of the array were jointly processed by the multichannel receiver with an oversampling factor $p = 2$. The length of the adaptive equalizer has been chosen to $L_f = 21$ so that the filter spans approximately two times the length of the significant part of the channel impulse response. The step-size μ_f of the CMA has been set to $2 \cdot 10^{-2}$. The results obtained from applying the proposed receiver to the experimental data are depicted in Figure 3.

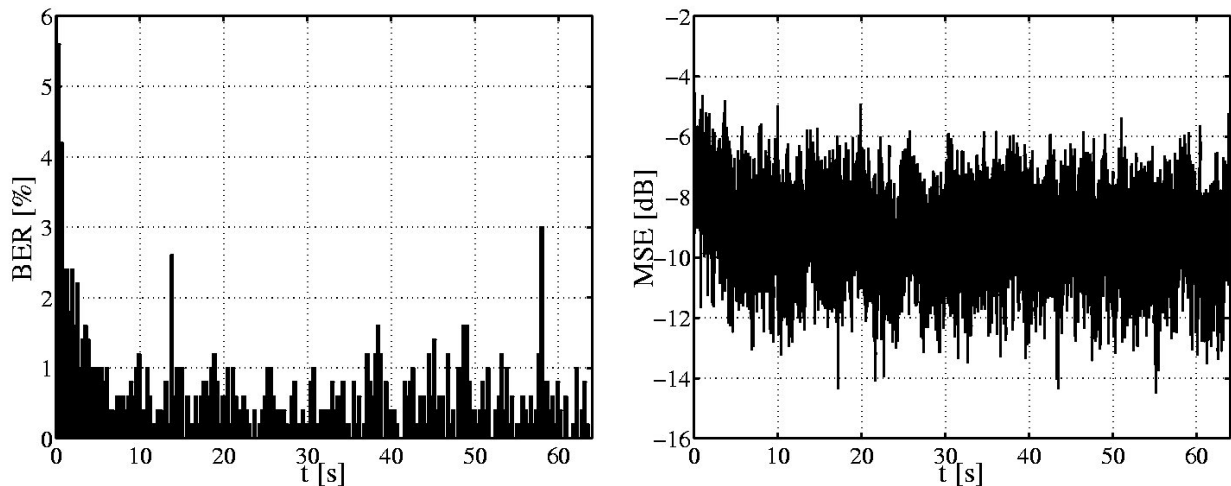


Figure 3: Results of multichannel blind CMA equalization

The estimated bit error rate (BER) over time is shown in Figure 3 – left. Each bar corresponds to the number of erroneous bits relative to 500 transmitted symbols. As can be seen, an initial BER of 6% is reduced to values below 1% within seconds. For the remaining transmission time, however, a considerable error floor remains leading to an average BER of 0.5 during the last 13 seconds. This slow convergence behaviour of the receiver is also reflected by the mean-square error (MSE), measured between the signals prior and after the decision device, which is shown in Figure 3 – right. Again, within seconds, the MSE reaches values of -9 dB, which is not further reduced in the sequel.

Additional experimental results are documented in [21, 24]. They all suggest that the multichannel constant modulus algorithm is well suited for blind space-time adaptive equalization of underwater acoustic communication channels. For a low SNR or severe linear distortion, however, it suffers from slow convergence due to saddle points of the underlying cost function. Therefore, the multichannel Shalvi-

Weinstein algorithm which is closely related to the CMA but exhibits far better convergence properties, is treated as an alternative in the next section.

5.0 SUPER-EXPONENTIAL BLIND EQUALIZATION

In [13], Shalvi and Weinstein have proposed a single-channel T -spaced² algorithm for blind equalization based on higher-order statistics. It is closely related to the constant modulus algorithm covered in the previous section and shares many of its positive attributes while exhibiting a super-exponential convergence rate [5]. The original iterative T -spaced algorithm has also been converted to a sequential one, allowing an adaptive implementation using empirical cumulants. An extension towards an iterative single channel fractionally-spaced equalization algorithm has been presented by Ding in [4]. Based on this approach, an algorithm for blind adaptive multichannel equalization has been developed in [22], which is summarized in the following.

5.1 Recursive Shalvi-Weinstein Algorithm

The fractionally-spaced super-exponential algorithm derived in [4] is an iterative batch algorithm that needs all available received data for joint processing. In a time-varying scenario, however, this is not desirable since different data segments may correspond to different channel impulse responses. It is therefore necessary to obtain an adaptive algorithm that sequentially processes the data and is thus also capable of tracking channel variations. We therefore propose an intuitive adaptive algorithm for multichannel, fractionally-spaced, super-exponential blind equalization that works purely sequential and is capable of converging without any initial training.

Omitting a detailed derivation the following quadratic cost function is introduced

$$J(n) = \sum_{n'=1}^n \beta^{n-n'} \gamma(n') \left| \frac{\sigma_a^2}{\gamma_a^4} \left(|y(n')|^2 - 2\sigma_a^2 \right) y(n') - \mathbf{f}_{L_f}^T(n) \mathbf{x}_{L_f}(n') \right|^2, \quad (16)$$

which has to be optimized with respect to the equalizer filter coefficients at each time instant n . In Eq. (16), σ_a^2 and γ_a^4 denote variance and kurtosis of the transmitted sequence $a(n)$, respectively, $0 < \beta \leq 1$ is the forgetting factor and $\gamma(n)$ is a general weight function. It has been shown in [24] that for a sufficiently high SNR minimization of (16) leads asymptotically to the optimal Wiener solution for the equalizer filter coefficients without using known reference signals. Comparing the cost function (16) with a classical MMSE approach [11], it becomes evident that the signal $(|y(n)|^2 - 2\sigma_a^2) y(n)$, generated from the received signal $y(n)$ by a non-linearity, plays the role of a reference signal. Instead of using a stochastic gradient descent approach to optimize the cost function as it was the case with the CMA, employing a recursive least squares approach leads to the update equation

$$\mathbf{f}_{L_f}(n) = \mathbf{f}_{L_f}(n-1) + \frac{\sigma_a^2}{\gamma_a^4} \alpha(n) e(n, n-1) \mathbf{k}(n) \quad (17)$$

for the equalizer filter coefficients, with the a-priori error signal $e(n, n-1)$ already given in Eq. (14). Comparing the update equation (17) of the Shalvi-Weinstein algorithm (SWA) with the corresponding equation (13) of the CMA shows the typical differences between an RLS and a stochastic gradient algorithm. While in the latter case the current data vector $\mathbf{x}_{L_f}^*(n)$ determines the direction of correction,

² In a T -spaced equalizer, $p = 1$, whereas in a fractionally-spaced equalizer $p > 1$, and in a multichannel equalizer $pN_C > 1$.

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the Kalman gain vector $\mathbf{k}(n)$ of the RLS algorithm is obtained by more complex operations and also depends on prior data vectors. The same holds for the step size $\alpha(n)$ that replaces the constant μ_f . It is therefore assumed, that the RLS algorithm leads to a better update estimation and thus a better convergence behaviour than a SGD algorithm.

Up to now, the influence of a carrier-phase offset has been neglected. From the formal correspondence between the constant modulus algorithm and the Shalvi-Weinstein algorithm it can be inferred that the latter is also invariant to a carrier-phase offset θ . Under the assumptions made, an already reconstructed signal constellation appears at the output of the equalizer, however rotating with a frequency $\Delta\omega$. This remaining rotation may again be compensated for by a decision-directed phase-locked loop.

5.2 Experimental Results

To enable comparison with the corresponding results in Section 4.2 obtained with the multichannel CMA, the same data set is now analysed with the Shalvi-Weinstein algorithm. Furthermore, the number of sensors ($N_C = 3$) and the length of the equalizer filter ($L_f = 21$) are kept constant. The forgetting factor β is chosen to $3 \cdot 10^{-3}$. The thus obtained results are summarized in Figure 4.

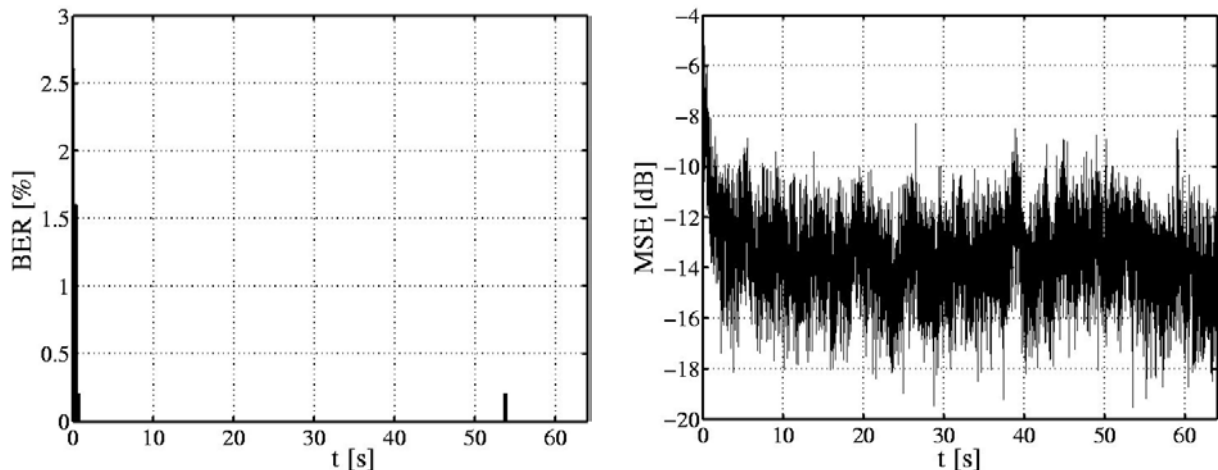


Figure 4: Results of multichannel blind SWA equalization

The estimated bit error rate is shown in Figure 4 – left. The comparison with Figure 3 – left shows the enhanced convergence properties of the proposed multichannel Shalvi-Weinstein algorithm: within one second the BER drops from an initial value of approximately 3% to virtually zero. This rapid convergence is also reflected by the mean-square error shown in Figure 4 – right. Again, within a few seconds, the MSE reaches values of -14 dB and below. Further results may be found in [23, 24]. Compared to the results obtained in [21], they all prove that the proposed multichannel fractionally-spaced superexponential algorithm outperforms the previously used multichannel constant-modulus algorithm.

6.0 CONCLUSIONS

In this contribution, we have focused on space-time adaptive processing in the context of blind equalization of underwater acoustic channels. To justify the great efforts in signal processing necessary to establish a reliable underwater communication link, special emphasis has been put on the characterization of the transmission medium. The typical underwater acoustic channel has been found to be overspread due to rapid temporal and spectral variations, therefore calling for special signal processing techniques. A

spatial-temporal receiver architecture has been introduced that efficiently allows for joint processing of signals received on many sensors. Based on this structure, a signal model suitable for the description of blind space-time adaptive equalization algorithms has been developed. Then, the well-known constant modulus algorithm for blind channel equalization has been treated as an example for the class of stochastic gradient descent algorithms. The results obtained with measured shallow-water communication data have demonstrated the general applicability of this algorithm but have also shown its slow convergence as a major drawback. As an alternative, an adaptive multichannel version of the Shalvi-Weinstein algorithm for blind equalization has been derived next. This algorithm is closely related to the constant modulus algorithm but shows a better convergence behaviour. This theoretically obtained result has been exemplarily verified by analyzing the same data set as with the CMA. Although in this paper we have presented two successful strategies for blind space-time adaptive equalization with applications to underwater acoustic communication, blind equalization is still an active area of research. In particular, for many proposed algorithms the bridge between theory and application is still lacking, constituting a rich set of research challenges for many years to come.

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