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On Adaptive Modulation for low SNR Underwater Acoustic Communications

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Abstract—This paper deals with adaptive underwater acoustic (UWA) communications where the receiver must operate at low signal-to-noise ratios (SNRs). The proposed modem is equipped with a set of direct sequence spread spectrum (DSSS) signals of various coding rates and modulation orders. A channel-estimate-based decision feedback equalizer (CEB-DFE) is used at the receiver. We address the challenge of achieving high spectral efficiencies subject to a combination of bit-error rate (BER) and SNR constraints. To this end, adaptive selection of signals is achieved based on their BER prediction via boosted trees. This ensemble of trees learns directly from the received data and relates the BER with signal characteristics and channel metrics. The efficiency of the boosted trees is validated by post-processing thousands of acoustic signals recorded in the Gulf of La Spezia, Italy. 10-20 times faster communications as compared to a modem with a fixed rate transmission is achieved.

Index Terms—Adaptive Modulation and Coding (AMC), machine learning, regression trees, Low Probability of Intercept (LPI).

I. INTRODUCTION

Underwater acoustic networks (UANs) typically cover a large geographic area and use acoustic signals to link the nodes together. The open nature of the acoustic channel allows unauthorized nodes to capture data or disrupt network functionality and therefore protection against security attacks is of paramount importance. *Eavesdropping* is a common type of security attack where an adversary uses a device that does not belong to the network to access to the contents of the communications message. The typical approach is to communicate at very low signal-to-noise ratio (SNR) by means of direct sequence spread spectrum (DSSS) modulation [1]. In this modulation technique, the information symbols are multiplied/spread by a code sequence resulting in a wideband transmitted signal. At the receiver side, the code sequence is used as a matched filter. Since the probability to detect a signal is SNR-dependent and the spreading code is known only to legitimate receivers, low probability of intercept (LPI) communication is said to be achieved with DSSS modulation at low transmit power.

A major challenge in applying DSSS in UWA communications is synchronization in the presence of long and time-varying reverberation. In [2], the authors have applied time-updated passive-phase conjugation (PPC) achieving a bit-error rate (BER) of 10^{-2} at -12 dB SNR. The same authors, have

applied incoherent detection of DSSS signals to achieve good communications at -10 dB [3]. In [4], the authors have tested spreading codes suitable for a coherent RAKE receiver. The reported performance is $5 \cdot 10^{-3}$ BER at -8 dB SNR. In [5], the authors have combined a Reed-Solomon code with M-ary orthogonal code keying (M-OCK) to achieve 35.63 bps at -14 dB SNR. In [6] a novel way to improve the LPI capability of communications based on chaotic sequences has been demonstrated. It is worthy to note that any coding technique that trades power for bandwidth can be used to enhance the LPI capability of the waveform. For example, the researchers in [7] have tested a multi-band equaliser system running on 1/3-rate turbo codes. The reported performance is 75 bps at -12 dB SNR with a single hydrophone.

An urgent requirement of LPI communications is the smart selection of the waveform length and bit rate that best fits the application requirements as well as the channel conditions. In other words, the tradeoff between throughput, reliability and target SNR needs to be quantified. Given the vast variety of underwater acoustic channels, closed-form formulas that predict the BER of a specific modulation technique based on the receiver characteristics are intractable in practice. Machine learning techniques that are purely data driven and capture the nonlinear effects (environmental and hardware-related) on the modem performance provide a promising avenue for developing adaptive modulation strategies. Some indicative machine learning techniques that have been applied for adaptive modulation and coding (AMC) in wireless radio are: neural networks [8], [9], support vector machines [10], decision trees classifiers [11] and kernel regression [12]. In the underwater acoustic domain, applications of machine learning algorithms are very scarce. A Bayesian inference algorithm has been applied in [13]. The same authors in [14] framed AMC as a multi-armed bandit problem to address the *exploration vs exploitation* dilemma. However, in both studies the channel state information available at the receiver was not considered to improve link adaptation.

Building upon our previous work presented in [15], we design a single-carrier modem equipped with seven DSSS signals of various bit rates. The goal is to transmit the signal with the maximal bit rate in the next transmission slot based on user-defined SNR and BER constraints. We use boosted trees

to learn the relationship between the measured BER with the signal parameters, the received SNR, and other related channel metrics which characterize the signal distortion. To validate our approach, we apply the boosted tree on a large amount of recorded signals transmitted during the Littoral Acoustic Communications Experiment 2017 (LACE17).

The paper is organised as follows. In Section II, the modem design and the experimental setup of LACE17 are presented. The proposed channel metrics that aid boosted trees to perform BER prediction are discussed in Section III. The BER results as well as the BER prediction capability of boosted trees are shown in Section IV. Finally, the paper is concluded in Section V.

II. MODEM DESIGN AND EXPERIMENTAL SETUP

We design a modem that is able to transmit and receive waveforms of different spectral efficiencies as a result of different coded modulation schemes, spreading sequences and baud rates. The transmitter block diagram can be seen in Figure 1(a). The information-bearing bit sequence is encoded and mapped into M-ary Phase-shift keying (PSK) channel symbols. For 2-PSK symbols, a 1/2-rate convolutional encoder is used. For 4- and 8-PSK symbols, Trellis Coded Modulation (TCM) with rate 1/2 and 2/3, respectively, is used. The PSK sequence is interleaved (shuffled) and then each PSK symbol is multiplied by a Kasami sequence of values -1 and +1. The resulting sequence $\{d(k)\}$ is pulse-shaped via a raised cosine filter with chip interval T and roll-off factor α . The baseband waveform is simultaneously modulated onto M carriers and transmitted in the water. The passband transmitted signal is given by

$$u(t) = \sum_k d(k)g(t - kT), \quad (1)$$

$$x(t) = \text{Re} \left\{ \sum_{m=1}^M u(t)e^{j2\pi f_m t} \right\}, \quad (2)$$

where $g(t)$ is the raised cosine pulse, $u(t)$ is the baseband signal and f_m denotes the carrier frequency for the m^{th} sub-band. Note the m^{th} passband signal occupies the frequency range $f_m \pm (1 + \alpha)/(2T)$. The carrier frequencies are chosen as follows [7]

$$f_m = f_c + (m - \frac{M+1}{2})B, \quad (3)$$

where B is the passband operational bandwidth and f_c is its middle frequency. Table I summarises the signals used in the modem. The signals BPSK-1, BPSK-2, BPSK-3, and BPSK-4 use 1/2-rate convolutional codes combined with 2-PSK. The signals QPSK-1 and QPSK-2 use 1/2-rate TCM codes combined with 4-PSK. The signal 8PSK-1 uses 2/3-rate TCM code combined with 8-PSK.

The block diagram of the receiver is shown in Figure 1(b). Initial processing involves shifting the acquired signal to baseband and coarse synchronization. Inter-chip interference due to time-varying multipath is tackled by our channel-estimate-based decision feedback equalizer (CEB-DFE). The

TABLE I
LIST OF SIGNALS.

Signal name	Kasami length	Baud rate (symbols/s)	Carrier (kHz)	Bit rate (bps)
BPSK-1	15	3500	10.4	116
BPSK-2	63	3500	10.4	27
BPSK-3	15	1750	9.26, 11.53	58
BPSK-4	63	1750	9.26, 11.53	13
QPSK-1	15	3500	10.4	233
QPSK-2	63	3500	10.4	55
8PSK-1	15	3500	10.4	466

CEB-DFE performs three sequential stages: (1) mean time scale compensation; (2) sparse channel estimation; (3) decision feedback equalization. Adaptation of these three processing stages is performed with a single estimation error. This error is the difference between the estimated M-ary PSK symbol (or chip, since the DFE operates on the spread sequence) before mapping and its value after mapping onto the signal constellation. At the beginning of each signal reception, the CEB-DFE runs in training mode and the true PSK symbols are known. After the training period, the on line decisions of the CEB-DFE are used to estimate the error. Channel estimation is performed in each sub-band independently via the Improved-Proportionate M-estimate Affine Projection Algorithm (IPMAPA). Joint sub-band equalization is performed based on the Recursive Least Squares (RLS) algorithm. The interested reader is directed to [16] for additional information. The soft symbol output of the CEB-DFE is permuted back (deinterleaving) to the original order before spreading. After de-interleaving the received sequence is matched filtered with the spreading code (de-spreading). The de-spread output is fed into the soft Viterbi decoder to compute the BER.

The BER performance of the modem was tested with acoustic data recorded from LACE17. The LACE17 trials took place between November 21st and November 25th in the Gulf of La Spezia, Italy. A map of the experimental area is shown in Figure 2. The depth of the area was about 10-12 m. Two sources were mounted on two rigid tripods 2 m above the seabed. The operational bandwidth of each source was about 8-12 kHz. In addition to the sources, four hydrophones were attached on each tripod at 50 cm, 1.1 m, 1.7 m and 2.3 m above the seabed. A third tripod with one hydrophone located 1.4 m above the seabed was also deployed. To test different ranges, one tripod with a source was deployed at different positions within the red area of Figure 2. As a result, the point-to-point links varied between 200 m and 800 m. It is important to mention two phenomena that took place during LACE17. The first is the occurrence of a storm with strong winds (about 5 m/s) during the 25th, which led to choppy seas. The second phenomenon is that the ambient noise was not stationary because of shipping and construction

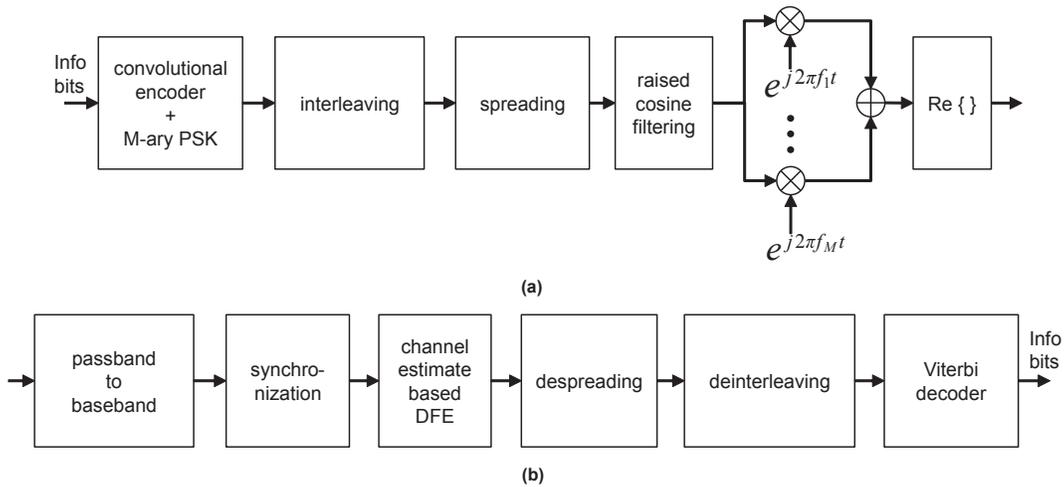


Fig. 1. (a) Transmitter block diagram. (b) Receiver block diagram.

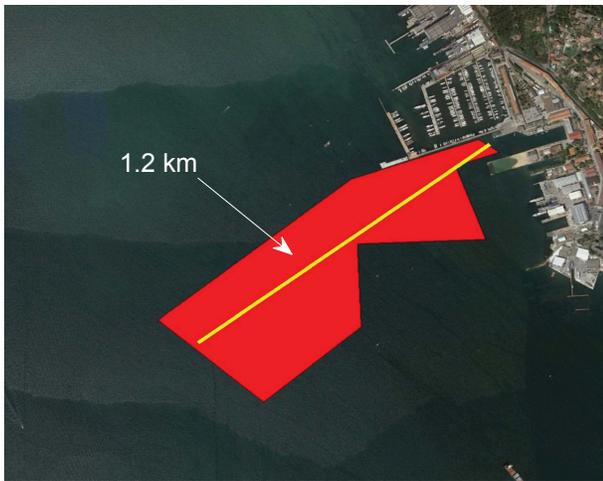


Fig. 2. LACE17: the red polygon indicates the experimental area in the Gulf of La Spezia.

(banging) activity. Moreover, we noticed that the ambient noise included instantaneous (impulsive) sharp sounds, which probably are due to snapping shrimp. Studies have shown that the Symmetric α -Stable ($S\alpha S$) distribution efficiently models snapping shrimp dominated noise [17].

Using the received signals as channel probes (i.e., running the CEB-DFE in training mode only), we provide insight about the variety of channel conditions during the sea trial. The received SNRs varied between 0-40 dB depending on the link range and the day time. Figure 3 shows the root mean square (RMS) delay spread [18] and the Doppler spread (averaged over all estimated multipaths) as a function of signal reception time. One notes that the delay spread ranges from few ms up to 30 ms. This bound is related to the particular shallow water environment: sound rays launched over steep angles experience high losses due to extensive reflections off the sea boundaries. Also observe that the Doppler variability between few Hz up to 20 Hz. Finally, the characteristic

exponent $\alpha \in (0, 2]$ of the $S\alpha S$ distribution of the ambient noise is shown with respect to the daytime. The characteristic exponent describes the impulsiveness of the ambient noise and smaller α manifests more impulsive noise. For $\alpha=2/1$ the $S\alpha S$ Probability Density Function (PDF) reduces to the Gaussian/Cauchy PDF, respectively.

From the above discussion, we conclude that our signals underwent significant distortions in both time and frequency domain due to time varying multipath propagation. These distortions are exacerbated by impulsive noise, which corrupts the signal at random short time intervals. Hence, achieving reliable communications in such an environment was challenging.

III. BOOSTED TREES FOR ADAPTIVE MODULATION

In wireless radio, there exist numerous analytic formulas that describe the BER as a function of the channel fading model. For instance, the authors in [19] derive BER closed-form expressions for Nakagami fading channels (which includes Rayleigh and Rician fading as special cases). Given the lack of consensus on channel models that relate the BER with waveform characteristics, this research adopts a pure data driven approach that will aid machine learning algorithms to accurately predict (regress) the BER. These techniques capture the intricate connection between informative channel/noise metrics and the BER. In this discussion, we assume that the BER is dependent on the following channel metrics:

- the received SNR, SNR_{in} , i.e., the ratio of total received signal power over the noise power,
- the output SNR, SNR_{out} , of the CEB-DFE [20]. It is known that the higher the SNR_{out} the better the equalisation of frequency selective fading, which in turn leads to suppressing inter-chip interference,
- the channel average fade duration (AFD). This is a measure of rapid time-selective fading and is typically defined as the number of times the received signal envelope falls

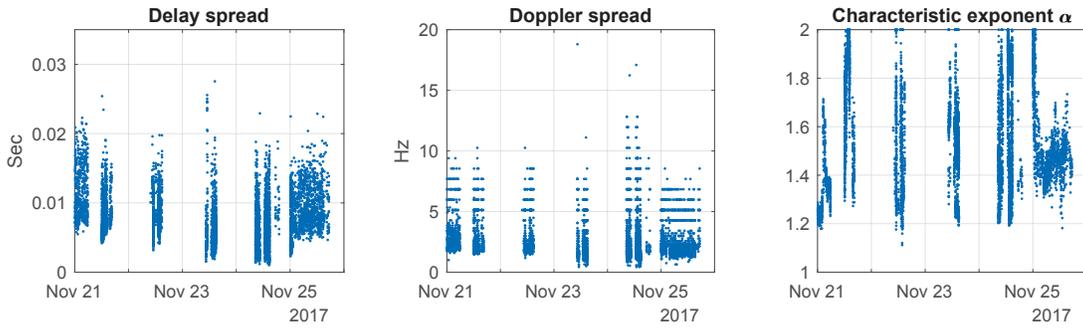


Fig. 3. LACE17: measurements of RMS delay spread, Doppler spread and characteristic exponent α .

below a certain threshold [21]. Here, the AFD is defined via the estimated channel energy,

$$E(t) = \int_{-\infty}^{+\infty} |h(t, \tau)|^2 d\tau, \quad (4)$$

(where t denotes the absolute time and τ stands for the multipath delay) and is equal to the duration for which $E(t)$ drops 3 dB below its maximal value. A channel with high AFD translates to a channel with deep fades, which in turn results to bursts of bit errors,

- the channel RMS delay spread (RMSDS) [18]. The RDS dictates the amount of inter-chip interference that the DFE needs to cope with,
- the Doppler spread (DS), which is a measure of the channel time-variability. The DS is computed as the average Power Spectral Density (PSD) over all multipath components (channel taps).

We frame the problem of BER regression based on the *input parameters*: signal name (implicitly includes coded modulation and bit rate, see Table I), the SNR_{in} (in dB), the SNR_{out} (in dB), the RMSDS (in seconds), the DS (in Hz), and the AFD (in seconds). The regression output can be generally, expressed as:

$$\hat{\text{BER}} = T(\text{signal name}, \text{SNR}_{in}, \text{SNR}_{out}, \text{RMSDS}, \text{DS}, \text{AFD}), \quad (5)$$

where $T(\cdot)$ is a regression tree.

Regression trees [22] recursively bisect the input parameter space to create binary partitions of the data, called *nodes*. Within each node, the regression tree estimates the BER as the average of the BER corresponding to the transmissions assigned to that node, thus minimizing the mean squared error (MSE) between the tree-predicted $\hat{\text{BER}}$ and the measured BER. To optimally bisect the input parameter space at each iteration, the training algorithm selects the input parameter and its associated value to maximally reduce the overall MSE in a given training dataset. This node-splitting procedure is repeated recursively until a desired MSE is achieved for the tree, or until a desired maximum tree depth is reached. The terminal nodes are called *leaf nodes*.

Regression trees can be used with heterogeneous datasets composed of numerical, categorical (different modulation

schemes in our case), and ordinal inputs, and can handle missing inputs transparently [22]. These two properties make trees one of the most versatile statistical learning methods currently in use. Yet, like other statistical learning techniques, regression trees can produce low-bias estimates but the estimates may be susceptible to high-variance.

To alleviate the high-variance problem, researchers in statistical learning have used ensembles of trees and achieved more robust estimates [22]–[25] compared to single trees. In boosted trees [26], the general learning technique *AdaBoost* [27] is applied to regression trees. Many trees are trained on the entire training data iteratively in such a way that at each iteration the training samples and the predictions are assigned weights adaptively, depending on the accuracy of the predicted values. The aggregated, final prediction from boosted trees is a combination of weighted predictions from each tree and the result is that the overall boosted tree classifier produces successively more accurate predictions as a function of the number of trees:

$$\hat{\text{BER}} = \sum_{i=1}^N w_i T_i, \quad (6)$$

where T_i is the i -th tree in the boosted ensemble and w_i its corresponding AdaBoost weight.

IV. RESULTS

The focus here is to find the implicit relationship between the BER and the considered channel metrics via boosted tree regression analysis. Recall that the experimental data were received in relative high SNR, which is not realistic for covert communications. For this reason, before decoding the data, simulated white Gaussian noise is added to each individual signal in proportion to its received SNR. We consider three target SNRs: 0 dB, -5 dB and -10 dB. These target SNRs are considered as three LPI regimes where the modem adapts its throughput. Extension to a larger number of SNRs is straightforward and is not considered in this work.

In what follows, we process 3704 audio signals that include all seven DSSS schemes in a sequential manner. Initial training of the DFE is performed based on a known transmitted PSK sequence of length 1000. Table II summarises the BER performance of each of the seven DSSS signals. As expected, the

TABLE II
BER OF SIGNALS.

	BPSK-4	BPSK-2	QPSK-2	BPSK-3	BPSK-1	QPSK-1	8PSK-1
bps	13	27	55	58	116	233	466
Number of signals	639	735	716	382	434	392	406
av. BER @ 0 dB	0.0086	0.0094	0.2998	0.0092	0.0046	0.0469	0.2359
av. BER @ -5 dB	0.0095	0.0197	0.4536	0.0106	0.0059	0.1188	0.3193
av. BER @ -10 dB	0.0596	0.1322	0.4767	0.0245	0.0296	0.2082	0.4664

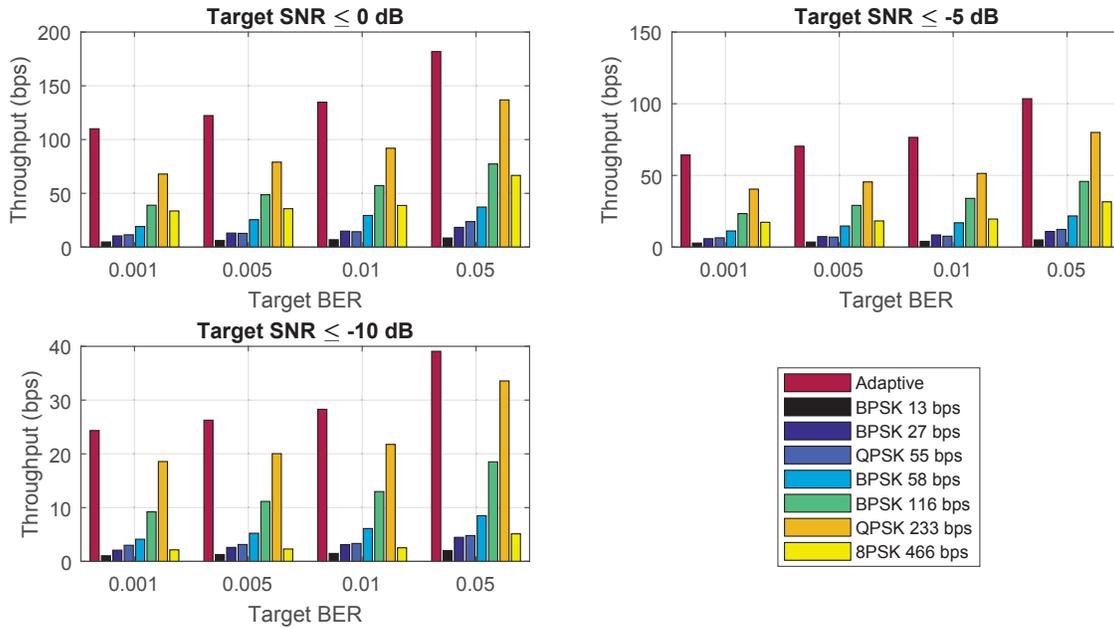


Fig. 4. Average signal throughput for different BER and SNR thresholds.

performance of each signal is degraded as the SNR decreases from 0 dB to -10 dB. Yet, our results show that the BER does not monotonically decrease with monotonically increasing bit rate. We believe that the proposed receiver has a difficulty in harvesting the full coherent spreading gain in channels with high time-variability (i.e., high Doppler spread). This issue happens because equalization and de-spreading are not jointly combined. This is the case, for instance, if one compares BPSK-4 (spreading length 15) with BPSK-1 (spreading length 65). Nevertheless, this does not impede an adaptive strategy to optimise the throughput since it is only dependent on the accuracy of BER predictions.

The dataset of Table II is arranged in a table of 11110 rows and seven columns. Every row i is populated with the input parameters: signal name $_i$, SNR $_{in_i}$, SNR $_{out_i}$, RMSDS $_i$, DS $_i$, AFD $_i$ and the output parameter BER $_i$. Note that there are two categorical inputs: the signal name and the SNR $_{in_i}$ (0 dB, -5 dB and -10 dB). The considered ensemble of boosted trees has 100 constituent trees and minimum leaf size of each tree is five. To validate the performance of boosted trees, we use disjoint sets for training and testing. In particular, we use 70%

of the data (7777 data points) for training and 30% (3333 data points) for testing. The rationale is to provide enough training data to learn the model sufficiently well, while ensuring that the test set is sufficiently large to capture the inherent variety of the data, allowing a thorough testing of the generalization capability of the trained model. The 70/30 split of the dataset is repeated 50 times and the average MSE of the BER prediction is found to be 0.0012. This is a fairly accurate prediction considering that the lowest BER achieved of our receiver is close to 0.005.

Our main result is to compute the average *signal throughput* of the modem based on the following working scenario. We assume that the modem has a trained model based on 70% of the dataset. The modem uses the testing set (30% of the data) to predict the BER of each DSSS signal. This is possible by changing the *signal name* parameter with the desired signal. The strategy is to select the DSSS scheme with the fastest bit rate such that its predicted BER is bounded by a BER threshold. After 50 random splits of the data, Figure 4 illustrates the average throughput for each of the considered target SNRs. The superiority of the adaptive scheme over each

fixed rate DSSS scheme is obvious for every SNR regime. Note, for example, that the adaptive scheme is about 10 times faster than 8PSK-1 (fastest but least reliable DSSS signal) and 20 times faster than BPSK-4 (slowest but most reliable DSSS signal) for a target SNR=-10 dB.

V. CONCLUSIONS

The results presented in this work aim towards developing a smart modem that will be able to boost its spectral efficiency (bps/Hz) in response to any channel conditions while retaining a desired level of covertness and reliability. To this end, we investigated boosted trees as a BER predictor based on field data. 3704 DSSS signals of different modulation orders and baud rates were transmitted during the LACE17 trials and our analysis showed that the boosted trees are efficient BER predictors. In addition, the boosted trees guided our adaptation strategy that yielded 10-20 times faster communications as compared to a modem with a fixed rate transmission. A critical extension of this work is to understand the impact of feedback delay on the throughput performance. This challenge will bring further insights on the robust application of boosted trees in real life scenarios.

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<i>Author(s)</i> Konstantinos Pelekanakis, Luca Cazzanti		
<i>Title</i> On adaptive modulation for low SNR underwater acoustic communications		
<i>Abstract</i> <p>This paper deals with adaptive underwater acoustic (UWA) communications where the receiver must operate at low signal-to-noise ratios (SNRs). The proposed modem is equipped with a set of direct sequence spread spectrum (DSSS) signals of various coding rates and modulation orders. A channel-estimate based decision feedback equalizer (CEB-DFE) is used at the receiver. We address the challenge of achieving high spectral efficiencies subject to a combination of bit-error rate (BER) and SNR constraints. To this end, adaptive selection of signals is achieved based on their BER prediction via boosted trees. This ensemble of trees learns directly from the received data and relates the BER with signal characteristics and channel metrics. The efficiency of the boosted trees is validated by post-processing thousands of acoustic signals recorded in the Gulf of La Spezia, Italy. 10-20 times faster communications as compared to a modem with a fixed rate transmission is achieved.</p>		
<i>Keywords</i> Adaptive Modulation and Coding (AMC), machine learning, regression trees, Low Probability of Intercept (LPI)		
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