Decision Tree-Based Adaptive Modulation for Underwater Acoustic Communications

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***Abstract*—Underwater acoustic channels are characterised by non-stationary fading statistics and consequently, a modulation scheme optimally designed for a specific fading model will underperform when the channel statistics change. This issue can be alleviated by using adaptive modulation, i.e., the matching of the modulation scheme to the conditions of the acoustic link. However, selecting signals from a broad range of bit rates is tedious because one needs to know the relationship between the bit error rate (BER) and all relevant channel characteristics (e.g., multipath spread, Doppler spread and signal-to-noise ratio). In this work, this BER-channel relationship is extracted from large amounts of transmissions of a phase-shift keying (PSK) modem. In particular, a decision tree is trained to associate channels with modulation schemes under a target BER. The effectiveness of the proposed tree method is demonstrated by post-processing data from two experimental links off the coast of Faial Island, Azores, Portugal.**

I. Introduction

Communication channels are typically categorized as power-limited or bandwidth-limited. This distinction is important because different modulation techniques are suitable for each channel. Power-limited channels yield a bit rate-to-bandwidth ratio less than one and require incoherent signaling, such as frequency-shift keying (FSK), to achieve reliable transmission. In contrast, bandwidth-limited channels can support several bits of information per Hz of occupied bandwidth thus achieving higher bit rates. Coherent modulation methods are Phase-shift keying (PSK) and Quadrature amplitude modulation (QAM). Adapting the modulation between coherent and incoherent methods is straightforward if the transmitter has knowledge of the received signal-to-noise ratio (SNR) [1].

Most commercial and military underwater acoustic communications channels fall into the bandwidth-limited regime. In this case, not only the SNR but also the channel multipath spread and Doppler spread dictate modem performance [2]. Since the physical properties determining sound propagation underwater are complex, it is almost impossible to find general probabilistic models for channel multipath/Doppler spread [3]. Hence, a system designed for fixed-rate PSK/QAM modulation will underperform over an extended period of time. One solution to this problem is to adapt the bit rate based on channel conditions provided that the channel fluctuates slowly during the two-way signal travel time.

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Studies that propose adaptive modulation in underwater acoustic channels are scarce. The authors in [4],[5] focus on single-carrier PSK modems while the authors in [6],[7] focus on orthogonal frequency division multiplexing (OFDM) modems. The central point in these papers is to identify the relationship between channel characteristics and system design.

This short paper presents the first attempt to use data mining for extracting the relationship between the BER and the acoustic channel characteristics. In particular, we use a decision tree (or regression tree) to learn the BER of a single-carrier PSK modem based on large amounts of transmissions at various bit rates. The effectiveness of the proposed tree method is demonstrated by analysing data from two links in a recent at-sea experiment.

II. Decision-tree aided adaptive modulation

We consider a single-carrier modem equipped with a number of transmission schemes. Assuming that the transmitter has channel state information, the goal is to find the scheme with maximal data rate for a target BER. The approach is to estimate relevant channel parameters (multipath/Doppler spread and SNR) at the receiver and transmit them back to the transmitter. Then a decision on the next transmission scheme is made based on the relationship between the BER of each signal and the channel parameters. The underlying assumption is that the channel varies very slowly with respect to the two-way signal travel time.

Since underwater acoustic channels are characterised by non-stationary fading, it is very tedious to derive a formula for the average BER for each transmission scheme. Here, we explore data mining based on large databases of channel probes occurred at different areas and seasons. In particular, we propose a decision tree [8] that can predict the BER of a digital modulation signal depending on the estimated channel parameters. Decision tree learning is conceptually simple yet powerful. The tree recursively partitions the space of input variables (i.e., channel/signal parameters) into a set of rectangles (binary partition) and fits a minimum square error (MSE) constant in each rectangle. The recursion is completed when the MSE falls below a threshold. Finding the best binary partition in terms of MSE is an NP-complete problem and so we use the greedy Classification And Regression Tree (CART) method [9].

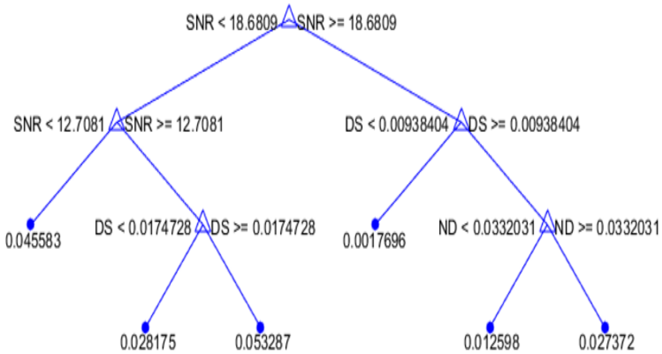

Fig. 1. Regression tree structure for predicting the BER of 8-PSK signals with various baud rates. The leaf nodes show the BER prediction. SNR is in dB, DS stands for the delay spread (ms) and ND stands for the normalized Doppler (Doppler spread $\times$ baud rate^{-1}).

TABLE I
SIGNAL PACKETS USED IN REP15 TRIALS.

Modulation	Band (kHz)	Duration (s)	Bit rate (bps)
2-PSK	10-15	1.22	4000
2-PSK	11-15	1.63	3000
2-PSK	11.9-14.1	2.45	2000
4-PSK	10-15	2.12	8000
4-PSK	11-15	2.83	6000
4-PSK	11.9-14.1	4.25	4000
4-PSK	12.4-13.6	8.50	2000
8-PSK	10-15	1.25	12000
8-PSK	11.9-14.1	2.50	6000
8-PSK	12.4-13.6	5.00	3000

An example of a decision tree tailored to adaptive modulation can be seen in Figure 1. The tree is trained by using a dataset of 343 signals. All signals are based on 8-PSK modulation but the bit rates range from 3000 to 12000 bps. The received SNR varies between 8 dB and 30 dB. In the text below, we provide details about these signals and describe the way we processed them. Traversing the tree from the leaf-nodes to the root-node, one can realize that the modem can achieve about 10^{-3} BER at maximum rate (12 kbps) only when the received SNR is larger than 18.6 dB and DS is smaller than 9.3 ms. Furthermore, at high SNR (>18.6 dB) and long DS (>9.3 ms), the BER depends on ND as well. Hence, the decision tree captures the tradeoff effect in increasing the baud rate. That is, higher baud rates induce more self-noise due to larger inter-symbol interference (ISI), however, they lead to better channel tracking since pulse period is smaller. Note that an advantage of a decision tree, with respect to a neural network, for example, is its simplicity in interpreting the results (the neural network behaves like a black box).

III. TRANSMISSION MODES AND RECEIVER STRUCTURE

In this short paper, we consider different transmission rates based on uncoded 2-PSK, 4-PSK and 8-PSK modulation. All information symbols are pulse shaped via a raised cosine filter with roll-off factor 0.25. Table I summarizes all signal types. The receiver structure can be seen in Figure 2. The receiver has three processing stages [10]: (a) motion-induced Doppler compensation; (b) inter-symbol interference (ISI) mitigation based on channel estimation; (c) adaptive linear equalization. Each PSK signal is shifted to basedband, low-pass filtered and coarsely synchronized based on a known chirp pulse. Motion compensation is achieved by adjusting the sampling rate at each symbol interval after extracting the phase rotation of the detected PSK symbol. Next, the resulting signal is used to produce an estimate of the channel impulse response based on the improved-proportionate normalized least mean square (IPNLMS) algorithm [11]. Combining past channel estimates with past transmitted symbols, an estimate of the post-cursor ISI is subtracted from the received signal. Then, the ISI-free signal is equalized by a linear filter producing a soft estimate of the transmitted PSK symbol. The taps of the feedforward filter are adapted via the exponentially-weighted recursive least-squares (RLS) algorithm [1]. Note that our receiver performs symbol-by-symbol adaptive resampling with symbol-by-symbol adaptive channel estimation in a closed-loop fashion. Consequently, fast platform motion is decoupled from slow environmental fluctuations leading to better channel estimates.

IV. REP15 DATA ANALYSIS

A. Data collection

The REP15-Atlantic experiment took place in the canal between the islands Faial and Pico, Azores, Portugal. Figure 3(a) shows the bathymetric data and Figure 3(b) shows the sound speed profile collected on July 8th, 2015. From the latter figure observe that there were three sound speed layers. A warm surface layer followed by an isospeed layer. Then, at about 20 m depth, the major thermocline starts causing downward refraction of sound rays. In this paper, we analyse data from three nodes, two transmitters and one receiver. All nodes were suspended at a depth of about 7.5-8 m. One transmitter was deployed off the NRP Gago Coutinho while the other was deployed off a rigid-inflatable boat (RIB). The transmit sampling frequency was 44.1 kHz. The receiver, was suspended off a moored gateway buoy. The receive sampling frequency was 96 kHz. The two transmitters were broadcasting the suite of signals of Table I at different time intervals for two hours (19:00-21:00 UTC). The signals arriving on the gateway buoy were stored for post-processing. Different ranges (500 m - 2 km) and platform velocities (0-3 knots) were tested in order to generate a rich dataset.

Here, we analyse 92 packet transmissions. The received SNR ranges from -1 dB to 35 dB. The receiver operates in training mode (i.e., the error that drives the equalizer is the difference between the soft symbol estimate and the transmitted symbol) to prohibit instability due to erroneous feedback.

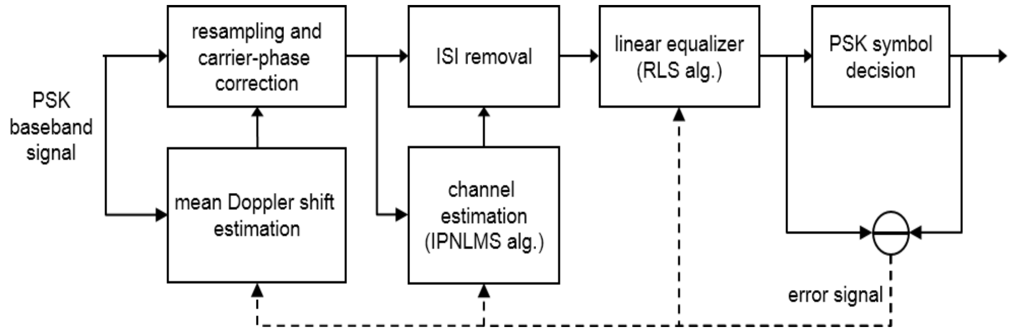

Fig. 2. Block diagram of the channel-estimate-based decision feedback equalizer (CEB-DFE).

For some of the encountered channels (e.g., high SNR), training mode mimics real-life scenario where the equalizer would run in decision directed mode while erroneous feedback would be alleviated by error correction coding. Furthermore, the issue of non-stationary fading is tackled by assuming short-term stationarity for hundreds of symbol intervals. In particular, the BER as well as the desired parameters (SNR, delay/Doppler spread) are computed after splitting the received signal into non-overlapping segments of 200 ms long. As a result, the number of processed 2-PSK, 4-PSK and 8-PSK signals becomes 429, 482 and 343, respectively.

To gain further insight about the channel conditions during REP15 trials, two channel impulse responses are shown in Figures 3(c) and (d). Motion-induced Doppler effects are removed and so any rapid variations are attributed to environmental changes. The 0 ms arrival corresponds to the direct path and the observed arrivals after 20 ms correspond to bottom/bottom-surface bounces due to the downward refracting sound profile. Note that both links exhibit sparse structure of arrivals, a feature that is exploited by the IPNLMS algorithm for improved channel estimation.

B. Decision Tree-based regression

A decision tree is trained to learn the BER of the PSK signals described above based on estimates of channel delay and Doppler spread and the received SNR. The tree depth is set to seven and the splitting process is stopped only when some minimum node size reaches at least 15 (BER) samples. The resulting tree has 16 terminal nodes (due to lack of space, the tree is omitted). For a target BER of about 10^{-3}, the tree indicates various strategies. The most interesting one is an interplay between 8-PSK and 4-PSK. In particular, the tree suggests that:

- if SNR>20 dB and the delay spread is less than 6 ms then choose 8-PSK at 12 kbps.
- if SNR∈[7 dB, 16 dB], the Doppler spread is less than 30 Hz and the delay spread is less than 10 ms then choose QPSK at 4 kbps.
- if SNR<4 dB then no modulation scheme is possible to achieve BER=10^{-3}.

Figure 4(a) provides the tenfold cross validation error of the BER prediction. At each run, 90% of the data is used for training the tree and the remaining 10% (test set) is used for prediction. In addition, each test set is chosen to be different across different runs and hence, all ten test sets combined represent the entire data set (1254 signals). From Figure 4(a) one can see that the mean and median of the error prediction is consistent across the ten runs, which indicates that the tree is robust to random sampling effects. Figure 4(b) illustrates the predicted BER when the tree is trained based on the entire data set. The mean of the prediction error is 0.0057, which is within the range of the mean value of the tenfold cross validation error.

V. Conclusion

This paper presents the first attempt to use data mining for adaptive modulation in underwater acoustic channels. We developed a decision tree capable of choosing the fastest data rate among a broad selection of single-carrier signals depending on channel state information. A dataset was recorded during the REP15-Atlantic experiment where PSK signals of various bit rates were tested under different channel conditions. A key step was to provide reliable channel estimates and BERs within short periods of time where channel fading was stationary. This step was achieved by using an adaptive equalizer that jointly performed motion compensation and channel estimation on a symbol-by-symbol basis. Our results demonstrated that the decision tree predicted the BER fairly accurately. Moreover, the tree identified thresholds for relevant channel parameters (SNR, delay/Doppler spread) required to achieve a target BER. From a practical standpoint, these results are very promising since they provide simple guidelines to a software-defined modem to switch fluidly between various transmissions schemes.

Acknowledgment

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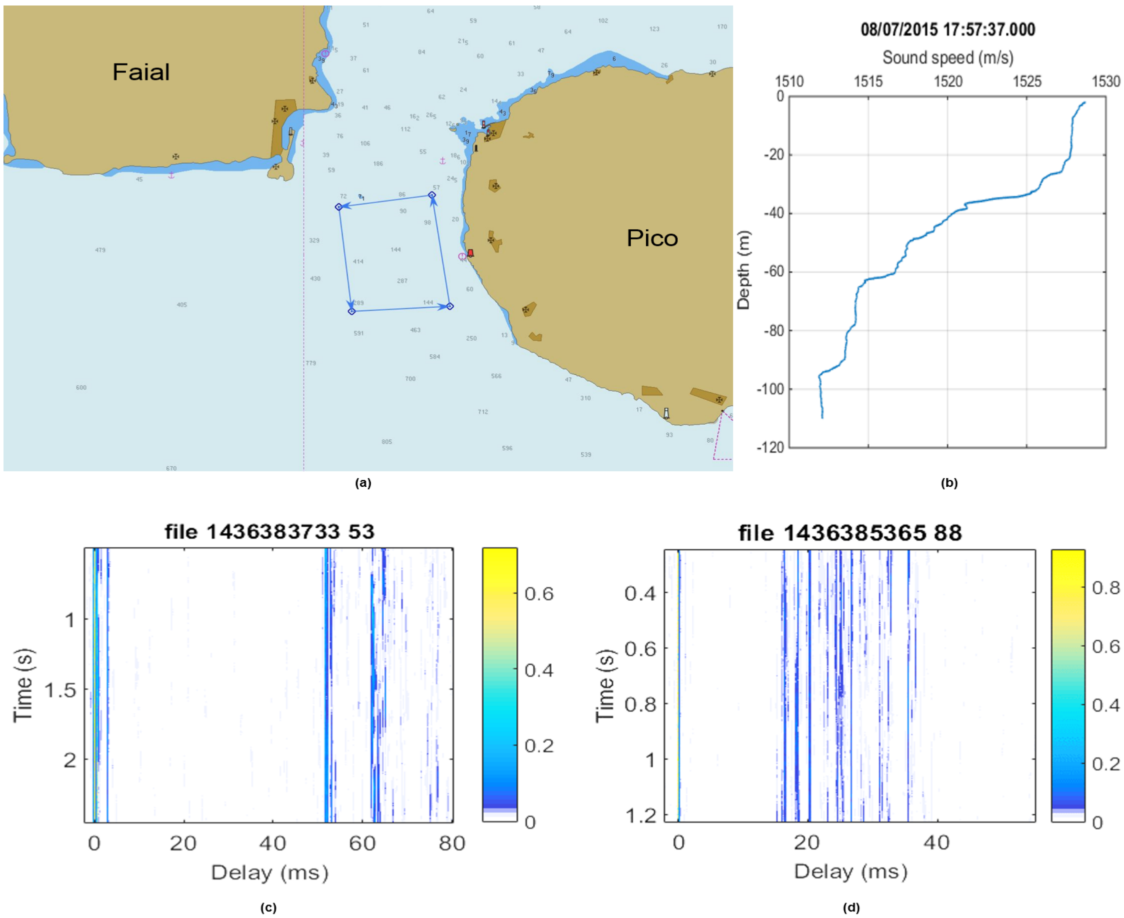
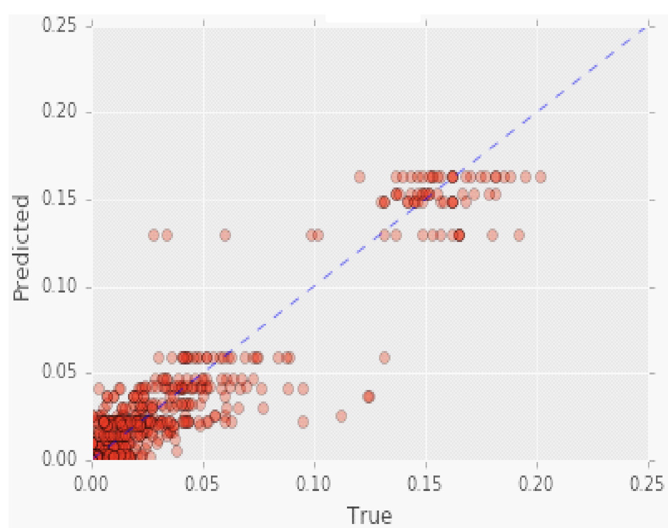


Fig. 3. (a) The area of operations is located between the islands Faial and Pico. The bathymetry ranges between 90 m and 400 m. (b) Sound speed profile collected on July 8th, 2015. (c) Time-varying impulse response corresponding to the link between NRP Gago Coutihno and the gateway buoy (range: 530 m, time: 19:29 UTC). (d) Time-varying impulse response corresponding to the link between the RIB and the gateway buoy (range: 1280 m, time: 19:57 UTC). For (c) and (d), the horizontal axis represents delay, the vertical axis represents absolute time and the colorbar represents the amplitude in a linear scale.

	mean	median	std	max
1	0.004972	0.001502	0.007887	0.037181
2	0.005444	0.001642	0.0076	0.038768
3	0.008629	0.001567	0.017176	0.1108
4	0.006149	0.001698	0.016032	0.140056
5	0.004997	0.001495	0.007607	0.049933
6	0.008777	0.002353	0.013889	0.107059
7	0.006487	0.001402	0.011507	0.066944
8	0.006384	0.001631	0.010314	0.045339
9	0.005832	0.001716	0.010019	0.053611
10	0.007569	0.001665	0.013948	0.100417

(a)



(b)

Fig. 4. (a) Tabulated tenfold cross validation of the BER prediction error. For each run (row), the mean, the median, the standard deviation and the maximum prediction error are shown. (b) True vs. predicted BER. The tree is trained on the entire dataset.

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