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Performance Analysis of Deep Learning based Signal Constellation Identification Algorithms for Underwater Acoustic Communications

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ABSTRACT

This research delves into the evaluation of Deep learning signal constellation identification (DL-SCI) algorithms in underwater acoustic communications using Orthogonal Frequency Division Multiplexing (OFDM). It distinctly examines at how effective the recurrent neural networks (RNNs), particularly, Gated Recurrent Unit (GRU) and Long Short-Term Memory (LSTM) algorithms in predicting the signal constellation when applied to different underwater acoustic channels characteristics. Unlike manual feature selection in machine learning (ML), in this paper, DL-SCI exploits the labelled OFDM signals at the transmitter to detect and decode them at the receiver. In order to measure their effectiveness performance metrics, Bit Error Rate (BER) and parameters derived from the confusion matrix such as accuracy and precision are used. The study highlights the importance of utilizing zero cyclic prefix techniques which can exploit the inherent bandwidth limitation effectively. Furthermore, when examining complexity, it is observed that both GRU and LSTM algorithms require less floating-point operations (FLOPS) compared to traditional methods such as Minimum Mean Square Error (MMSE) and Least Squares (LS). Interestingly GRU shows performance in terms of complexity when compared to LSTM. Moreover, GRU outperforms LSTM by achieving a 4 dB improvement for long subcarriers. These results emphasize the effectiveness of learning techniques in enhancing performance and efficiency in acoustic communications.

1. Introduction

In the field of wireless communication, the effectiveness of OFDM systems greatly depends on channel estimation methods [1]. Underwater acoustic channels have not been recognized yet, thus predicting the channel impulse response (CIR) is crucial and needs sophisticated approaches such as in [2]. Identifying signals [3], particularly, in channels with an inherent Doppler effect [4], poses a significant challenge because of the intricate and ever-changing nature of the underwater surroundings. Over the years, deep learning, specifically recurrent neural networks (RNNs) have emerged as a promising method to improve the dependability and precision of signal detection and classification tasks [5]. This article explores supervised RNN based learning with a focus on comparing two architectures; LSTM and GRU. The research utilizes acoustic channels to fine tune and evaluate the effectiveness of these systems. Notably using communications as the testing environment adds a unique and demanding aspect to this comparative study distinguishing it from traditional signal constellation research. Through this study we aim to shed light on how LSTM and GRU

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architectures perform in the realm of signal constellation, laying the groundwork for dependable and effective communication systems, in aquatic settings.

As a result, there is significant attention being given to leveraging machine learning (ML) algorithms to transform communication systems. Communication systems that have been in use for a time typically rely on known and traditional models [6]. Hence algorithms utilized for channel estimation necessitate a comprehension of channel statistics. For instance, the minimum mean square error (MMSE) algorithm. However, machine learning (ML) algorithms introduce a data driven approach to the realm of communications that goes beyond relying on channel statistics [7]. This aspect makes ML algorithms highly valuable in scenarios where modeling channel statistics proves to be challenging. Nevertheless, ML necessitates manual feature selection, thus DL manifest itself as a promising solution for low complexity constellation learning.

1.1 Contribution

The contributions of this paper are:

1. The article examines two known deep learning methods, LSTM and GRU in the context of processing acoustic signals.
2. The study investigates the effectiveness of LSTM and GRU architectures in channels providing insights into their performance across various environmental conditions.
3. The article talks about using a zero cyclic prefix, in (OFDM) to enhance communication systems. This approach has shown to be successful, in environments leading to better data transmission reliability and bandwidth efficiency.
4. The research paper showcases how removing the cyclic prefix in OFDM can improve the effectiveness and dependability of communication systems, tackling the obstacles presented by the marine environment.
5. The study shows that deep learning methods, like LSTM and GRU are simpler than techniques, in analyzing underwater signals. This suggests that using deep learning algorithms can make constellation learning in settings straightforward and efficient.

1.2 Paper organization

The paper is organized as follow: the related works is presented in section 2. Then, section 3 presents the adopted system model and related background. Next, deep learning-based signal constellation is depicted in section 4. After that, section 5 shows the proposed DL-Based Signal constellation Identification. The simulation results are depicted and analysed in section 5. Finally, section 7 presents the conclusions.

2. Related works

This section summarizes research that utilizes deep learning algorithms along OFDM signals, particularly in the underwater acoustic environment.

Yıldırım, Mahmut [8] introduce an approach called PTS AIM, which is based on a Tabu Search (PTS) algorithm, for OFDM with All Index Modulation (OFDM AIM). The PTS AIM method aims to enhance the Bit Error Rate (BER) performance by searching for the constellation point for each subcarrier. Additionally, a signal detection system named DeepAIM is proposed, combining a Long Short-Term Memory (LSTM) algorithm, with a Deep Neural Network (DNN). Lastly a novel architecture called PTS DeepAIM integrates the PTS AIM and DeepAIM approaches. Simulation results demonstrate that PTS DeepAIM surpasses AIM in both BER performance and computation time attributed to its design incorporating the PTS based look up table and DL based signal detection architecture.

Jebur, Bilal A. et al. [9] explore the possibility of creating machine learning techniques for channel estimation in 6G communications. The suggested algorithm combines with frequency division multiplexing to remove inter-symbol interference. The article investigates the algorithms resilience, intricacy and convergence while showcasing the achieved outcomes. Furthermore, it delves into the applications of this research, in communications. Signal detection with reduced complexity based on neural network is presented in Ref. [10].

Furthermore, Zhang, Yuzhi et al. [11] suggest using a deep learning approach to detect signals, in UWA Orthogonal time frequency space (OTFS) communication. By training a network the system can successfully reconstruct the transmitted symbols. This method combines a network (CNN) with skip connections (SC) and a bidirectional long short-term memory (BiLSTM) network for signal retrieval. The technique leverages information from received OTFS signal sequences to train the network for detecting signals. Results show that the SC CNN BiLSTM based OTFS detection method outperforms methods, like 2D CNN, FC DNN and conventional signal detection in terms of Bit Error Rate (BER).

Besides, the impact of a specific optimization technique known as" early stop" in the implementation of the proximal policy algorithm within the openai/spinningup library is presented in Ref. [12]. The main concept behind early termination methods is to assess the extent to which the policy changes during each update and avoid updates that lead to sudden and drastic policy changes. In this version of early stop, which is called KLE Stop, the updates will be halted if the KL divergence, between consecutive updates exceeds a predetermined threshold.

Yufei Liu, Yunjiang Zhao et al. [13] introduce a method, for communication using binary frequency shift keying and variable Doppler frequency hopping based on deep transfer learning (DTL). The system employs a CNN as the demodulation component of the receiver. of estimating the Doppler this approach directly demodulates the received signal. The DTL first trains the CNN using simulated communication signal data. Then transfers some convolution layers from a trained CNN to the target CNN. The remaining layers in the target CNN are initialized randomly. Trained using data samples from communication scenarios. Throughout training the CNN associates frequencies with symbols in selected frequency hopping groups via Mel spectrograms. Results from simulations and experimental data processing demonstrate that this proposed system outperforms systems, particularly when both transmitter and receiver are moving at varying speeds, in water acoustic environments.

Mohammed AS et al. [14] created a simulated environment to assess the performance of OFDM under various channel conditions. To achieve this, different models have been utilized. Furthermore, a learning technique has been utilized to make an estimation of the channel by leveraging data from training. Two types of channel models are utilized to compare their effectiveness.

There is an endeavour to employ learning techniques in addressing wireless channels without requiring real time training is presented in Ref. [15]. The outcomes of the simulations demonstrate that deep learning models can achieve performance to conventional methods when there is an adequate number of pilots in OFDM systems. Moreover, these models exhibit better performance, with a limited number of pilots, CP free.

Chen, Jie and Liu et al. [16] introduce a data focused method, for signal separation through the use of deep learning technology. It employs a bidirectional short-term memory (Bi LSTM) technique to analyze the characteristics of a time frequency (T-F) mask and proposes a T- F mask aware Bi LSTM model for signal separation. By leveraging the sparsity of the T-F image the developed Bi LSTM network can extract features for separation leading to performance in separating signals. Notably this approach surpasses methods by achieving outcomes in multivariate separation and effectively isolating signals even when mixed with 40 dB Gaussian noise signals. Experimental findings demonstrate that this method can ensure a 97% guarantee ratio (PSR) with the average similarity coefficient for multivariate signal separation exceeding 0.8 in high noise scenarios.

A new approach has been introduced in Ref. [17]. This study for estimating channels, in UWA OFDM systems using learning and clustered structure information. Initially a cluster identification model employing networks is presented to detect the clusters within UWA channels. This method surpasses the Page test algorithm in terms of accuracy and resilience under low signal to noise ratio circumstances. Furthermore, a channel estimation technique that considers clusters and utilizes distributed sensing is proposed based on the cluster detection model. By narrowing down the search space for channel delay spread and leveraging sparsity among neighbouring OFDM symbols, this method helps minimize errors caused by noise. Results, from simulations and sea trials, indicate that the proposed approach outperforms sparse UWA channel estimation methods.

Zhang et al. [18] introduced a new approach to make it unnecessary to estimate the CSI. The method involves sending two known labels from the tag before transmitting data. By analyzing the information, in the received signal constellation a modulation constrained expectation maximization algorithm was suggested. This led to the development of two detection methods. One method involves learning parameters by grouping the labelled signals and then using these parameters to recover the signals. The second method uses all received signals for clustering. Efficient initialization techniques are included for both algorithms. Simulation results demonstrate that these constellation learning methods perform similarly to the detector, with CSI.

To address the classification challenges of traditional CNNs, Ref. [19] proposed training on phase and quadrature (IQ) samples of OFDM signals. They incorporate a dropout layer to prevent overfitting and enhance identification accuracy. Furthermore, the validation of the trained CNN was achieved using datasets with modulation modes. The experiments demonstrate that their proposed method offers accuracy and consistency compared to methods. Additionally comprehensive results affirm the performance of their approach across datasets.

Peng, Shengliang et al. [20] explore the application of (DL) in modulation classification as an aspect in various communication systems. DL eliminates the need for feature selection thereby simplifying the complexity involved in modulation classification tasks. The research utilizes two DL models based on networks (CNNs); AlexNet and GoogLeNet. Various techniques are developed to represent modulated signals in grid data formats for CNN analysis. The study also investigates how different representations impact classification performance. Includes comparisons, with cumulant based and ML algorithms.

M. Abdul Aziz et al. [21] suggested a detection method using a neural network, for OFDM-Index modulation (OFDM-IM). A detection approach based on (LSTM) to boost the bit error rate (BER) performance of the OFDM-IM system was presented.

All aforementioned researchers have focused on a traditional type of the wireless channels with CP-OFDM. In the proposed system, zero cyclic prefix is adopted with the OFDM which reduce the overhead and offer a bandwidth. In addition, two types of real channels have investigated to confirm the system reliability.

3. System model and background

A scenario of two communication points is involved in sharing data over a connection is adopted. To prevent any disturbances caused by the connection, a method known OFDM is conducted. This technique helps prevent intersymbol interference (ISI) that might arise due to the nature of the connection.

3.1 OFDM signal generation

Let us think about the OFDM signal in the time domain at time i created by applying inverse Fast Fourier transform (IFFT) to $X_i(k)$ with N subcarriers, where k is the subcarriers index. It is postulated that the signal undergoes modulation, through M-ary quadrature phase shift keying (QPSK). This signal composite of pilots and guard interval defined as a cyclic prefix (CP). Although this guard interval is important to mitigate the inter-symbol interference due to the channel effect, it consumes the bandwidth, which is already limited in the underwater communications, Consequently, the transmitted OFDM vector $x_i = [x_1, \cdots, x_N]$.

3.2 Received signal and channel model

The transmitted signal is sent over a multipath fading channel with characteristics shown by

$$c(\tau, t) = \sum_{l=0}^{L-1} h_l(t)\delta[\tau - \tau_l(t)] \qquad (1)$$

where $h_l(t)$ are the path amplitudes, $\tau_l(t)$ are the time-varying path delays and L is the total number of paths [22]. The path delays τ_l and the gains h_l, were assumed constant over the frame duration T.

Once the channel (1) is convolved with the transmitted signal, the received signal is given as

$$y = [y_1, \cdots, y_K], \in \mathbb{C}^{1\times K} \qquad (2)$$

where, K is the number of packets, and $\mathbb{C}$ refers to a set of complex numbers.

4. DL-Based signal identification

In this section, two types of RNN algorithms have demonstrated superior performance than traditional methods of estimating channels and neural network paradigms [23], particularly in handling extensive input data. Additionally, the structural design of these learning algorithms is detailed herein.

4.1 LSTM structure

The LSTM architecture is an advancement, in neural networks especially for handling sequences of data. As shown in Figure 1.

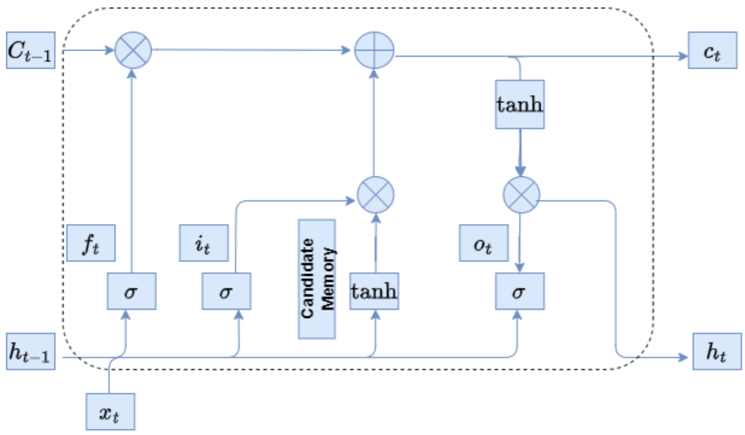


Figure 1. LSTM structure

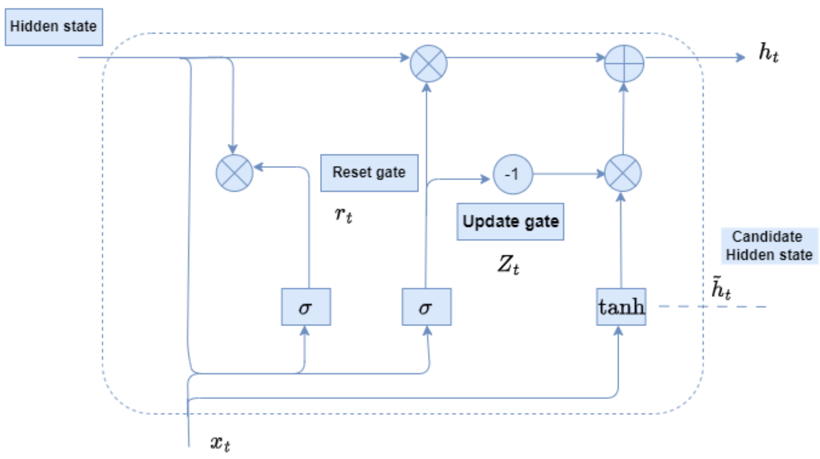


Figure 2. GRU structure

LSTM essentially involves an interplay of gates and memory cells to capture and remember long term dependencies [24]. The forget gate in (3), driven by a sigmoid function σ determines what information to discard from the memory cell state, while the input gate in (4) decides on information to incorporate. The cell state in (5) is then updated by combining the decisions from both gates. Finally, the output gate in (6) controls which parts of the updated cell state are revealed as the output. These precise operations have made tools in various fields such, as natural language processing, speech recognition and time series analysis. The LSTM equations can be formulated as [25]:

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right) \tag{3}$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i), \tilde{C}_t = \tanh\left(W_c \cdot [h_{t-1}, x_t] + b_c\right) \tag{4}$$

$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t \tag{5}$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o),\ h_t = o_t \odot \tanh\left(C_t\right) \tag{6}$$

where b_f, b_i, b_c,and b_o are the bias parameters and W_f, W_i, W_c , and W_o denote weight parameters, $\odot$ represents element wise multiplications.

4.2 GRU structure

The Gated Recurrent Unit (GRU) is a type of (RNN)network that is great, at capturing patterns over time in sequential data [25]. In each time step t the update gate z_t in (7) decides the amount of data to keep in the previous hidden state h_{t-1} , see in Figure 2. Additionally, the reset gate r_t in (8) manages how much to forget from the state. The potential hidden state $\tilde{h}_t$ in (9) is then calculated based on the reset gate and the current input x_t. Ultimately updating the state involves a mix of the hidden state h_t in (10) and the potential hidden state, determined by the update gate. The GRUs smart design allows it to effectively handle long term relationships, in data while staying efficient computationally.

$$z_t = \sigma(W_z \cdot [h_{t-1}, x_t]) \tag{7}$$

$$r_t = \sigma(W_r \cdot [h_{t-1}, x_t]) \tag{8}$$

$$\tilde{h}_t = tanh\ (W_h \cdot [r_t \odot h_{t-1}, x_t]) \tag{9}$$

$$h_t = (1 - z_t) \odot h_{t-1} + z_t \odot h_t' \tag{10}$$

where W_z, W_r, and W_h are the weight parameters. The GRU algorithm architecture is promising compared to LSTM due to the following reasons: (i) GRUs merge the forget and input gates into an update gate reducing parameter count and computational complexity in comparison, to LSTM networks. This streamlined approach enables training and inference without compromising performance. (ii) The update and reset gates found in GRUs play a role in controlling the information flow and addressing the issue of vanishing gradients often encountered in RNNs. This mechanism helps maintain stability across sequences allowing the network to better grasp interdependencies. (iii) GRUs have parameters compared to LSTMs making them less susceptible to overfitting, which's particularly beneficial when working with smaller datasets. This feature improves their ability to adapt to tasks and areas.

5. The Proposed DL-Based signal constellation identification

In this section, we briefly talk about the development of RNN cells that have demonstrated performance compared to networks, in handling lengthy input data.

5.1 Data set

The data used in this research forms the core dataset for training LSTM and GRU deep learning models. Both models undergo training using the datasets and simulations of sound channels, with QPSK modulation to extract features for comparative analysis. To predict signal identification a crafted dataset is created using QPSK modulation to assess the strength of the proposed system. Various Signal to Noise Ratio (SNR) values from 0 to 50 dB are tested, with each modulation symbol consisting of 25,000 packets for both training and testing. With 128 OFDM subcarriers allocated for data and an additional 128 subcarriers, for pilot signals, the resulting dataset includes 256 components totalling 512 values representing each received packets features. This extensive dataset is then fed into the network during training or utilized in time to predict signal constellations.

5.2 Offline training

In Figure 3, the pilots and data get inputted into the OFDM transmitter to create a sequence of n frames. These frames are sent out after undergoing channel convolution processing. The transmitted pilots are then used in an LS estimator to compute an estimated channel. The LS estimation is then utilized as one of the inputs, for training the estimators.

At the front end of the receiver shown in Figure 3, there is a stage called preprocessing, in which the data is prepared by converting it from serial to parallel and applying Fast Fourier Transform (FFT). These results, in generating a collection of imaginary components, for the data packet, which forms the characteristics of the received information. These attributes are fed into the system to create a pattern. The training and testing phases are illustrated in algorithm 1. The procedure showcasing how learning (DL) networks handle both imaginary values. The DL networks can be described using an input vector.

$$Y(n) = [\Re(Y(n)), \Im(Y(n))]. \quad (11)$$

where, $Y(n)$ is a pre-processed received data and the transmitted QPSK symbol labels can be formulated as:

$$S(n) = \left[e^{\frac{\pi}{4}}, e^{\frac{3\pi}{4}}, e^{\frac{5\pi}{4}}, e^{\frac{7\pi}{4}}\right]. \quad (12)$$

Algorithm 1 DL-Based signal constellation algorithm

Stage 1: Offline Training

1. Generate data for the transmitted signal which consist (Pilot, subcarriers, labels).
2. Compute fading channel coefficient using (1).
3. Convert data to packet (pilot and data).
4. Compute integer FFT for each packet.
5. Detect the received signal using (2).
6. Convert $\boldsymbol{tx}$ packet and $\boldsymbol{rx}$ packet to features (target)
7. Formulate the transmitted packet to labels (Target).
8. Combine data set to construct feature for DL algorithm to train the dataset.
9. Train the network
10. Save

5.3 Online training

This phase shown in algorithm 2, in this phase, the primary focus is, on utilizing learning models in time for communication systems. During this process neural networks that have been trained in algorithm 1 play a role in adjusting signal constellations to adapt to the changing conditions encountered during data transmission. These conditions may involve variations in channel characteristics, interference and noise levels in such environments. Through learning and optimization, the online phase aims to improve the resilience, reliability and overall efficiency of communications using OFDM technology. The ultimate objective is to ensure the transmission and reception of data packets, in unpredictable underwater scenarios.

Algorithm 2 DL-Based signal constellation algorithm

Stage 2: Online Training

1. Load Trained network.
2. Convert received packet to feature.
3. Estimate constellation labels using DL classifier.
4. Convert label to constellation.

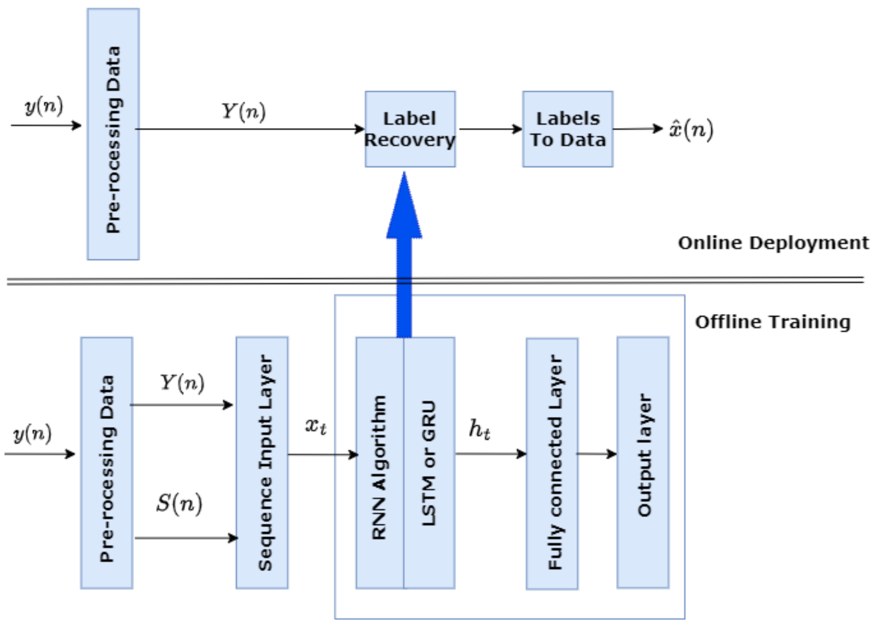


Figure 3. The proposed system model

6. Simulation results

All deep learning parameters and steps are depicted in in Table 1. In this simulation, the performance of the proposed signal identification was investigated over two multipath channels. In addition, two factors have been considered to measure the severity of these channels, delay spread τ_l and its magnitude h_l. As shown in Table 2, the delay spreads were 3.5 ms and 6 ms of channel 1 and channel 2, respectively. However, the amplitude of the direct path for channel 1 was highest that channel 2. Comparison with MMSE and LS to check the performance was conducted. The length of subcarriers is firstly tested then the effect of pilot subcarriers is also investigated.

Table 1: Deep learning algorithm setting

Parameter	Value
Input layer	1
LSTM or GRU	16 Layers
Fully connected layer	4
Softmax layer	Softmax layer
Classification	output layer

Table 2: Channels path delays and magnitudes

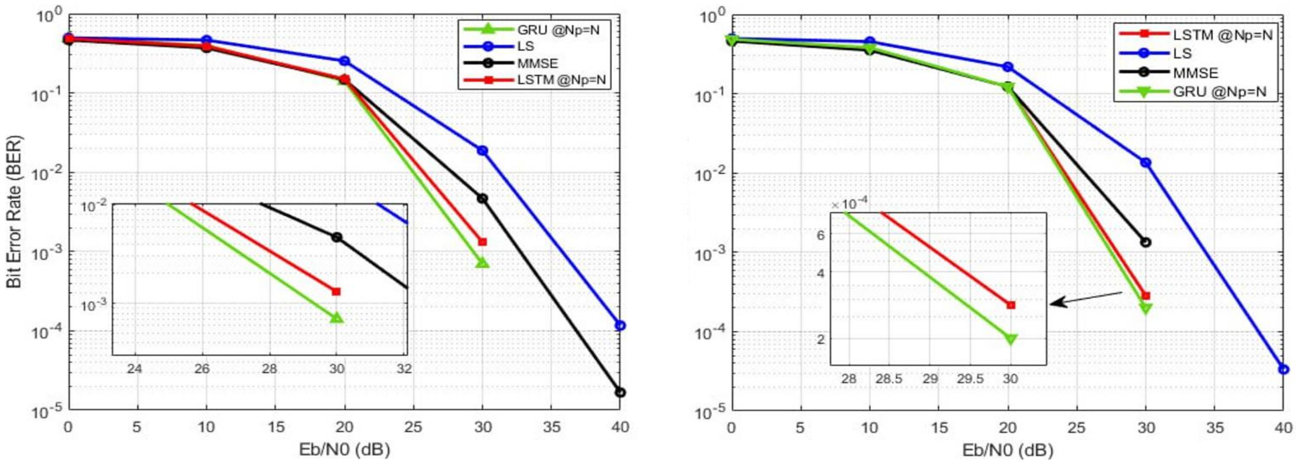
Channel 1		Channel 2	
τ_l(ms)	$h_l(t)$	τ_l(ms)	$h_l(t)$
0	0.7106	0	0.6529
0.125	0.5441	0.7500	0.4406
0.625	0.3252	1.1250	0.3869
1.000	0.2011	1.3750	0.3105
2.625	0.1766	2.1250	0.2699
3.000	0.1398	3.7500	0.1737
3.500	0.0449	4.1250	0.1481
-	-	5.7500	0.0752
-	-	6.0000	0.0536

6.1 Bit error rate (BER)

In Figure 3, the pilots and data get inputted into the OFDM

In Figure 4 (a), when the SNR is set at 30 dB for example the BER of the GRU model is around 0.0001 while the LSTM model shows a higher BER of about 0.001. This indicates that with 64 subcarriers the GRU model performs better in terms of error rate compared to the LSTM model, under these conditions. In Figure 4 (b) it can be observed that at signal to noise ratios (around 28 dB and above) all the models show low bit error rates (below 0.0001). The effectiveness of all the models gets better as the SNR increases. The data indicates that the GRU model using 128 subcarriers performs better in terms of BER compared to the LSTM, MMSE and LS estimators, at 30 dB. Nonetheless the performance gaps narrow down when considering 64 subcarriers. The GRU model outperforms LSTM, MMSE and LS estimators, in terms of achieving a lower Bit Error Rate (BER) at an Eb/N0 value of around 30 dB in both scenarios involving 64 and 128 subcarriers. The improvement in BER with the GRU model is more pronounced for 64 subcarriers compared to 128 subcarriers. For example, at 30 dB the BER for the GRU model could be 0.0001 for 64 subcarriers and about 0.000028, for 128 subcarriers. It seems like boosting the quantity of subcarriers from 64, to 128 could enhance the BER performance across all models (GRU, LSTM, MMSE and LS). This might be due to the fact that having more subcarriers enables increased data transmission and improved channel estimation. However, the advantage of subcarriers appears to be less noticeable, for the GRU model. Even though the BER gets better with 128 subcarriers the difference compared to 64 subcarriers is not as significant. The analysis indicates that the GRU model shows performance, in both situations, with 64 and 128 subcarriers. It seems to excel especially with 64 subcarriers.

Figure 5 compares the results obtained from the preliminary analysis of DL algorithms on channel 2. From this figure, it can be seen that the GRU algorithm has lower BER than LSTM in all pilot subcarriers densities $N_p = 25\%N$, $N_p = 50\%N$ and $N_p = N$, respectively. After analyzing the figure, it is evident that the GRU algorithm (represented by the dotted blue line) shows a notable improvement of 4 dB, in BER performance compared to the LSTM algorithm (depicted by the dotted red line) in situations with high pilot density. This difference becomes especially noticeable when there is a cluster of pilot subcarriers, for estimating the channel. This discovery differs from what was found in [9], where having a pilot density decreased performance in terms of BER. The design of the GRU could work well for making use of a set of data for estimating channels. Its gating system might help in extracting the channel details, from numerous pilot subcarriers.



(a) 64 subcarriers (b) 128 subcarriers

Figure 4. BER performance comparison of Deep learning algorithms (GRU and LSTM) with MMSE and LS over channel 1 at CP=0 with different subcarriers

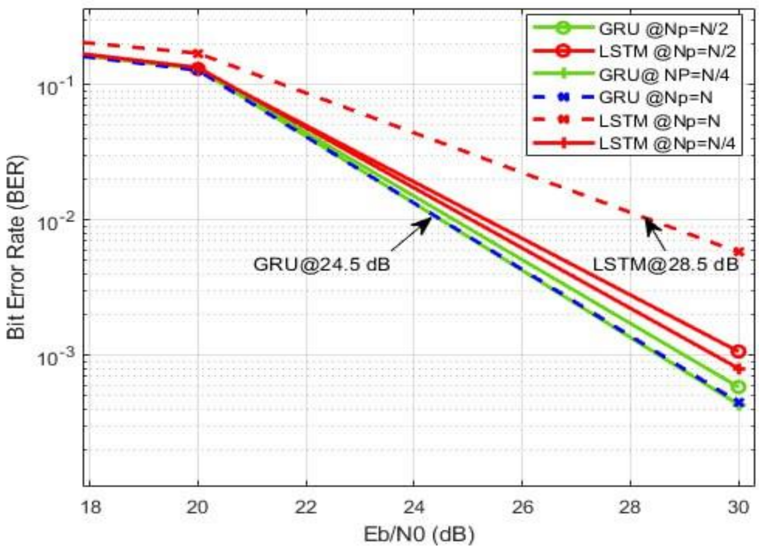


Figure 5. BER performance comparison of GRU and LSTM over channel 2 at CP=0, $N = 128$ and different pilot subcarriers $N_p = \frac{N}{4}$, $N_p = \frac{N}{2}$ and $N_p = N$

Figure 6 presents the performance comparison between two DL algorithms (GRU and LSTM) over different channel conditions at CP=0 and CP=16. In channel 1 the GRU and LSTM models showed accuracy and precision. Both models achieved, around 99.834% (GRU) and 99.85% (LSTM) accuracy at cyclic prefix 0. Precision values remained consistently high for all classes in both models. Moving on to channel 2 both GRU and LSTM models displayed performance as seen in channel 1. At cyclic prefix 0 both models reached 99.85% accuracy. Both channels (1 and 2) demonstrated performance with the GRU and LSTM models across cyclic prefixes. Any slight differences in metrics between the channels are likely due to varying channel characteristics, noise levels, interference or environmental factors. Nonetheless overall both models proved to be effective, across channels and cyclic prefixes showcasing their resilience and dependability under circumstances. The differences, in performance between the channels with cyclic prefix 16 resemble those seen with cyclic prefix 0. There are variations in accuracy and possibly in precision, values for certain categories. These variances may stem from differences, in channel delay spread.

6.2 Confusion matrix

In this section, we contrast the effectiveness of GRU and LSTM models by examining the confusion matrices acquired for channel 1 and channel 2, at CP=0. These matrices offer insights into how each model classifies data allowing for a thorough assessment of their performance, in various channel settings. As demonstrated in Table 3 for channel 1, the GRU model showed performance, with True Positive rates for all classes effectively categorizing samples in each class. The LSTM model also performed well although it had TP rates than the GRU. Both models had False Positive and False Negative rates indicating their capability to reduce misclassifications. In general, the confusion matrices for channel 1 indicate that both the GRU and LSTM models are effective, in this channel setting. In comparison to channel 1 the GRU model, on channel 2 depicted in Table 4 experienced a drop in rates for certain categories, specifically class 1 and class 4. On the hand the LSTM model showed true positive rates across all categories demonstrating its strong performance. Although both models had positive and false negative rates the GRU model had slightly higher false positive rates than the LSTM model. The data from channel 2s confusion matrices indicates that the LSTM model performs better than the GRU model, in this particular channel setting.

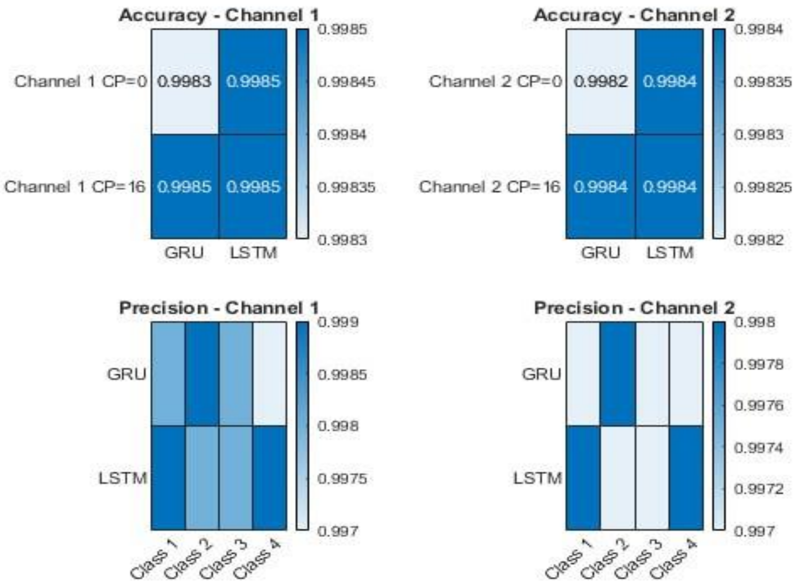


Figure 6. Accuracy and precision comparison under different channel conditions and different CP length

Table 3: Confusion matrix summary for channel 1, CP=0 @30dB

Model	Class	True Positive (TP)	False Positive (FP)	False Negative (FN)	True Negative (TN)
GRU	1	7522	4	3	4471
	2	7503	3	6	4467
	3	7516	3	4	4467
	4	7447	2	1	4467
LSTM	1	7438	7	4	4461
	2	7425	4	4	4467
	3	7472	2	2	4464
	4	7448	3	3	4469

Table 4: Confusion matrix summary for channel 2, CP=0 @30dB

Model	Class	True Positive (TP)	False Positive (FP)	False Negative (FN)	True Negative (TN)
GRU	1	7421	1	9	7691
	2	7362	7	0	7421
	3	7499	4	5	7472
	4	7691	0	2	7421
LSTM	1	7175	77	58	7101
	2	7273	57	14	7175
	3	7148	25	41	7160
	4	7101	3	30	7175

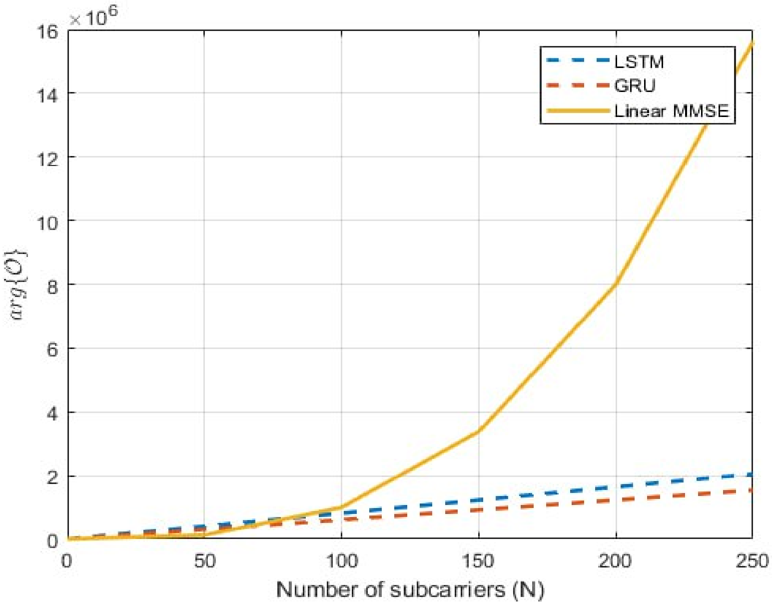


Figure 7. Computational complexity comparison of ML estimator and LMMSE

6.3 Complexity analysis

LSTM unit is comprised of three gates. The input gate, forget gate and output gate along, with a memory cell. These gates control how information moves within the unit deciding whether to keep or discard data as time progresses. On the hand GRU units are less complex, than LSTM units featuring two gates combined into one, the reset gate and update gate. Additionally, GRU units include a state that gets updated at each time interval. Figure 7 shows that GRU and LSTM models are usually less complex than MMSE models, which require $\mathcal{O}(N^3)$ floating point operations for matrix inversion and vector multiplications. Although MMSE models have shown effectiveness in most scenarios, their demanding computational needs can limit scalability and practicality in band-limited environments, especially underwater. This is why the straightforward nature of GRU and LSTM architectures makes them choices for situations where maintaining a balance, between efficiency and model performance's crucial. LSTM units are often seen as intricate due to their gates and memory cell. The use of memory cells and multiple gating mechanisms leads to increased complexity which can be represented as $C_{LSTM} \approx \mathcal{O}(4h_s^2N)$ [25]. On the hand GRU units are viewed simpler than LSTM because they have fewer parameters and computations $C_{GRU} \approx \mathcal{O}(3h_s^2N)$ The absence of a memory cell and the integration of gates into a single update gate help reduce the complexity of the GRU structure. Despite its design the GRU has demonstrated performance compared to LSTM in various tasks such as sequence modelling. GRUs are particularly preferred in situations where there are constraints, on resources or when quicker training is desired.

7. Conclusions

In summary, this research has offered insights, into how well deep learning-based signal constellation methods perform in using OFDM for acoustic communications. By comparing the (GRU) and (LSTM) algorithms on two acoustic channels with different delay spreads several important discoveries have been made. To start with the use of zero cyclic prefix techniques has proven to be very beneficial leading to reductions in overhead and saving bandwidth which is usually limited in the reality of underwater environment. Additionally, examining complexity has shown that both GRU and LSTM algorithms require floating point operations than traditional methods such as Minimum Mean Square Error (MMSE) and Least Squares (LS). Notably GRU shows a performance in terms of complexity compared to LSTM. Furthermore, when it comes to Bit Error Rate (BER) performance GRU outperforms LSTM by achieving a 4 dB gain. This is due to the gating architecture of the GRU network. For these reasons, the GRU is more effective at ensuring signal reliability and efficiency, in acoustic communications. By tackling issues, like weakened signals and restricted bandwidth these methods provide opportunities to boost the dependability and performance of communication networks. Subsequent studies could delve deeper into using learning for acoustic-based communications concentrating on overcoming more obstacles such as the Doppler effect compensation and fine-tuning system operations.

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