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CHANNEL PREDICTION FOR UNDERWATER MIMO COMMUNICATIONS USING ADAPTIVE BIDIRECTIONAL GATED RECURRING UNIT

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ABSTRACT

As the realm of the Internet of Things (IoT) continues to evolve, niche applications such as underwater communication are gaining momentum both in academic and industrial spheres. Within this context, the utilization of multiple-input multiple-output (MIMO) technology holds immense importance for bolstering channel capacity in underwater acoustic (UWA) communication setups. Accurately forecasting channel responses emerges as a critical aspect for ensuring optimal system functionality. This paper introduces a streamlined model for predicting channel impulse responses (CIRs) tailored specifically for UWA MIMO communication scenarios. Dubbed the small adaptive bidirectional gated recurrent unit (ABiGRU) network, our model exhibits the ability to discern channel characteristics without necessitating intricate knowledge of internal channel properties. The proposed approach leverages short-term CIR data for real-time training, subsequently enabling accurate predictions to track the dynamic nature of UWA channels. To validate our methodology, we integrate space-time block coding (STBC) with minimum mean square error (MMSE) pre-equalization within the UWA MIMO framework. Our simulations demonstrate the practicality of this scheme, showcasing low bit-error rates (BER). Furthermore, we conduct an extensive evaluation of our ABiGRU network's prediction accuracy vis-a-vis the widely employed MMSE algorithm and other recurrent neural network (RNN) variants like gated recurrent units (GRU) and long short-term memory (LSTM). Real-world experiments in UWA MIMO settings underscore the superior performance of our ABiGRU network, suggesting its potential for cost-efficient deployment in underwater IoT sensor networks.

Keywords: adaptive bidirectional gated recurrent unit, multiple input multiple output (MIMO), internet of underwater things (IoUT).

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1. INTRODUCTION

In the realm of underwater communications, the ability to predict channel conditions accurately holds paramount importance for ensuring reliable and efficient data transmission. The dynamic and harsh underwater environment poses significant challenges to conventional communication systems, necessitating innovative approaches to overcome these obstacles. Multiple Input Multiple Output (MIMO) New-age systems have emerged as a promising solution, utilizing spatial diversity to bolster communication performance.

However, the effectiveness of MIMO systems critically depends on the accurate prediction of underwater channel characteristics. Traditional channel prediction techniques often fall short in capturing the dynamic nature of underwater channels, characterized by multipath propagation, Doppler shifts, and temporal variations. As a result, there is a pressing need for advanced prediction methods tailored specifically for underwater Multiple input multiple output communications.

This study introduces a pioneering method employing Adaptive Bidirectional Gated Recurrent Units (GRU) for channel prediction within underwater MIMO systems. GRU, a subtype of recurrent neural networks (RNNs), demonstrates proficiency in modeling sequential data and capturing temporal dependencies, making it well-suited for predicting time-varying channel conditions. By incorporating bidirectional processing and adaptability mechanisms, our proposed model aims to enhance prediction accuracy and robustness in a challenging underwater environment.

This study aims to achieve two primary objectives: firstly, to establish a robust channel prediction framework using Adaptive Bidirectional GRU specifically designed for underwater MIMO communications, and secondly, to assess the effectiveness of the proposed method compared to existing prediction techniques through extensive simulations and real-world experiments. By fulfilling these objectives, our goal is to advance underwater communication systems, thereby enhancing reliability and throughput in real-world deployment scenarios.

In the following sections, we will delve deeper into the methodology employed for model development, detailing the architecture of the Adaptive Bidirectional GRU and the training process. Furthermore, we present experimental results and performance evaluations, followed by discussions on the implications of our findings and potential avenues for future research. Through this research endeavour, we strive to pave the way for enhanced underwater communication capabilities, addressing the burgeoning demands of diverse applications ranging from ocean exploration to underwater surveillance and resource monitoring.

2. BACKGROUND

The idea behind this project originates from the crucial requirement for strong and efficient wireless

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communication technologies to cater to the needs of modern applications. These include tasks like high-speed data transfer and the rise of autonomous systems. MIMO technology holds the potential to significantly enhance both spectral efficiency and reliability while incorporating RNNs can offer advanced signal processing capabilities. Understanding how these techniques work together is essential for advancing wireless communication technologies. In this project, we aim to explore how Multiple Input Multiple Output (MIMO) technology and Recurrent Neural Networks (RNNs) interact within wireless communications. Our motivation comes from the growing importance of dependable and efficient communication systems in various applications today. Whether it's the need for fast data transfer or the increasing use of IoT devices, innovative solutions are needed to improve efficiency and reliability. MIMO technology shows promise by using multiple antennas for simultaneous data transmission and reception, which boosts overall system performance. Combining this with RNNs adds sophisticated signal processing capabilities, making communication systems more adaptive and intelligent. Our project focuses on finding new ways to improve wireless communication systems by integrating MIMO technology and RNNs seamlessly. This exploration is driven by the increasing demands of modern applications, which require robust, efficient, and adaptable communication frameworks. With the rise of IoT and autonomous systems, there's a greater need for reliable wireless communication. By studying how MIMO technology and RNNs work together, we aim to discover new methods and insights that can push communication systems forward. Through rigorous experimentation, analysis, and validation, our aspiration is to contribute to the advancement of communication technologies, fostering a more interconnected and intelligent world.

MIMO Systems:

MIMO systems harness the power of multiple antennas at both the transmitter and receiver ends to enhance communication performance through the utilization of spatial diversity. This diversity leads to increased data rates and enhanced link reliability.

Recurrent Neural Networks (RNNs):

RNNs, or recurrent neural networks, are a category of artificial neural networks specifically engineered to handle sequential data. Their design makes them highly effective for tasks that involve analyzing time-series data and processing signals. In the realm of wireless communications, RNNs find application in tasks such as equalization, channel estimation, and interference cancellation.

3. EXISTING METHODS

Several methods for predicting channels in underwater acoustic communications have been proposed, each with its own set of limitations. The minimum mean square error (MMSE) algorithm, for instance, is effective in predicting frequencies in MIMO-OFDM systems but comes with a high computational cost due to the necessity of large matrix inversions, rendering it impractical for many applications. On the other hand, the recursive least squares (RLS) algorithm offers an adaptive approach to calculating the parameters of a linear predictor in the time domain, providing reasonable tracking capability with a simple design. However, this method of channel impulse response (CIR) prediction only takes into account the magnitude of channel taps, neglecting the variation in channel delay. This limitation is particularly problematic in underwater acoustic networks with extensive sensor node deployments, such as the Internet of Underwater Things (IoUT).

4. ANTICIPATED SYSTEM

We introduce a novel, compact, and adaptive bidirectional gated recurrent unit (ABiGRU) network designed to capture real-time channel information in underwater acoustic (UWA) environments. Our model utilizes short-term channel impulse responses (CIRs) obtained from channel estimation for online training, enabling it to predict CIRs and effectively track the dynamic nature of UWA channels over time. To enhance overall communication performance, we propose a combination of space-time block coding (STBC) and minimum mean square error (MMSE) pre-equalization, leveraging the predicted CIRs. Numerical analysis reveals that STBC significantly enhances the performance of multiple input multiple output (MIMO) systems, particularly in noisy and fading channels. By transmitting multiple copies of the signal stream over multiple hydrophones with time delay and phase shifts, we achieve notable diversity gains, leading to improved error rates and reliability.

5. RESULTS AND CONCLUSIONS

Overall Results

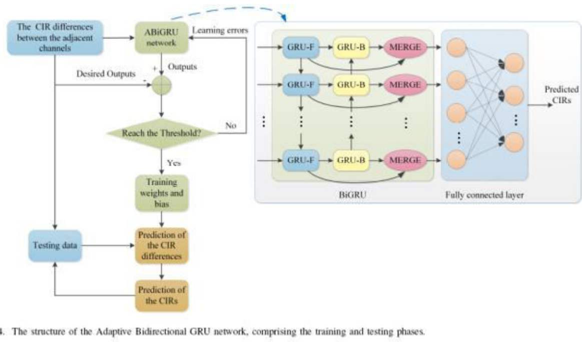

Figure-1. Comparison of MMSE, LSTM, GRU, and ABIGRU's MSE vs prediction index.

In Figure-1, we compare the Mean Squared Error (MSE) of MMSE, LSTM, GRU, and ABiGRU models against the prediction index. It is evident that when keeping the prediction index constant, ABiGRU exhibits the lowest MSE among the models. A lower MSE indicates a more stable system, highlighting ABiGRU's superior performance compared to others. The MMSE approach hinges on an estimated signal-to-noise ratio

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(SNR), which may often diverge from the actual SNR. This discrepancy in estimated values can lead to significant deviations in performance. Moreover, as we base our CIR predictions on the variance between predicted CIRs at the current and preceding time steps, any prediction errors accumulate over time, especially with rising prediction indexes.

Table-1.

MODEL	MSE	Prediction index
MMSE	0.00403	8
LSTM	0.002614	8
GRU	0.002287	8
ABIGRU	0.002178	8

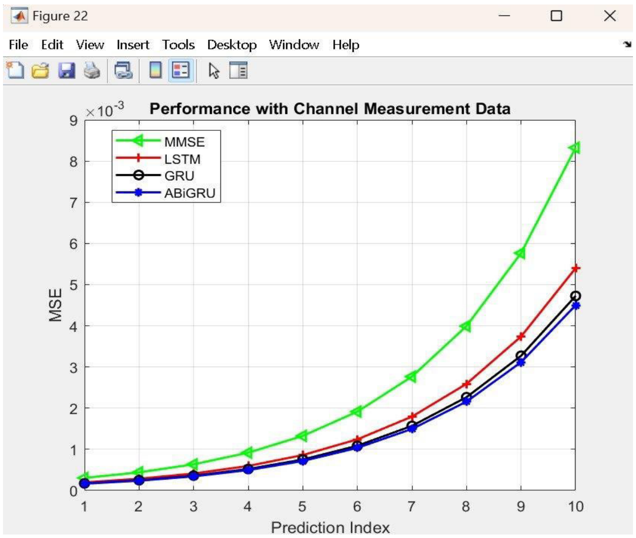

Figure-2. Effects of the number of units in the hidden layer.

Examining Figure-2, we explore the impact of varying the number of units (Nn) within the proposed ABiGRU network on prediction errors. The graphical representation illustrates a decline in Mean Squared Error (MSE) with an increase in the number of units in the neural network. Consequently, guided by these results, we elect to employ 256 units, provided ample hardware resources are at our disposal.

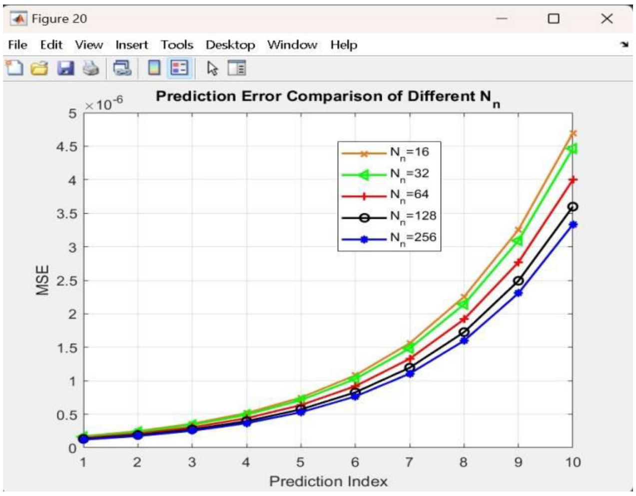

Figure-3. Effect of the length of training sequences Nt.

Figure-3 illustrates the comparison of Mean Squared Error (MSE) against the prediction index for ABiGRU, varying the length of the sequence. Notably, the MSE decreases with longer sequences. Specifically, the ABiGRU model with Nt = 500 demonstrates superior performance, leveraging a larger pool of training samples. Broadly speaking, augmenting the number of training samples typically leads to improved performance of the ABiGRU model during the training phase.

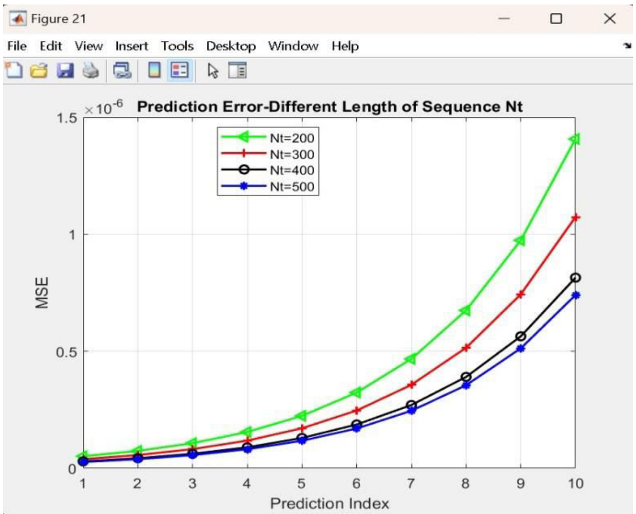

Figure-4. Performance comparison with different numbers of the known length p based on the channel measurement data.

Figure-4 illustrates how the known history length (P) influences prediction errors based on channel measurement data. At prediction index 10, the Mean Squared Errors (MSEs) for ABiGRU are 0.0044 for P=10, 0.0042 for P=20, 0.0039 for P=30, and 0.0036 for P=40. The results indicate a noticeable enhancement in performance with an increase in the known history length (P).

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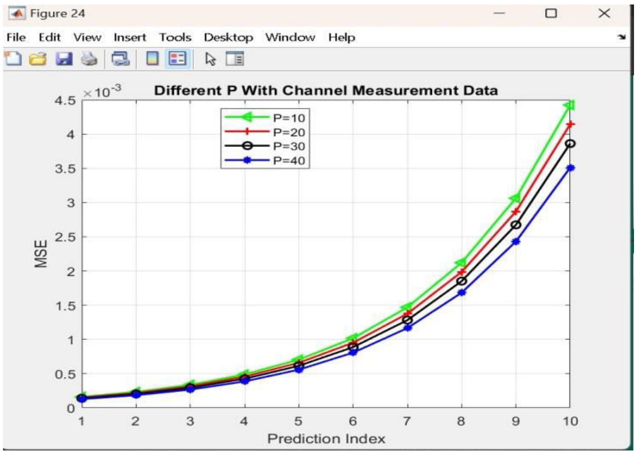

Figure-5. BER comparison of different RNNs.

Figure-5 illustrates the assessment of predicted Channel Impulse Responses (CIRs) utilizing adaptive LSTM, GRU, and ABiGRU models in the context of the STBC-MMSE pre-equalization scheme. The outcomes distinctly reveal the superior performance of the ABiGRU model compared to the others, showcasing the lowest Bit Error Rate (BER) values across diverse Signal-to-Noise Ratio (SNR) levels in a 2x2 Underwater Acoustic (UWA) MIMO system. Moreover, the BER derived from the GRU-based predictor surpasses that of the LSTM-based predictor, underscoring the efficacy of varied neural network architectures in this context.

Table-2.

MODEL	BER	SNR
LSTM	0.004495	4
GRU	0.001334	4
ABIGRU	0.008894	4

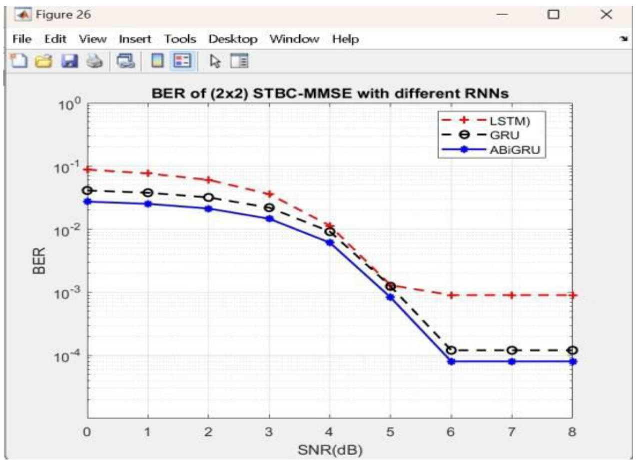

Figure-6.

Figure-6 illustrates plots comparing different equalization methods based on Bit Error Rate (BER) values versus Signal-to-Noise Ratio (SNR). The comparison encompasses the MMSE pre-equalization method with M = 2, N = 1, the STBC-MMSE pre-equalization scheme with M = 2, N = 1, and the STBC-MMSE pre-equalization scheme with M = 2, N = 2. Each scheme's performance exhibits distinct BER values, with the aim of achieving lower BER values for a reliable model. Particularly noteworthy is the STBC-MMSE scheme with M = 2, N = 2, demonstrating the lowest BER rate among the compared methods, thereby indicating its effectiveness in enhancing system reliability.

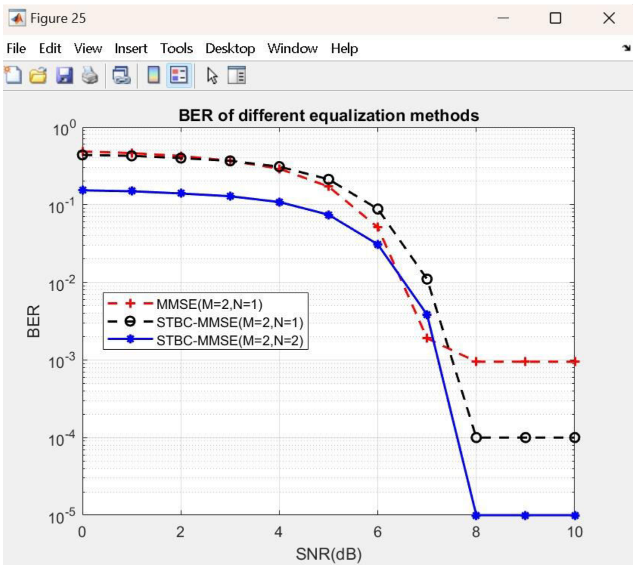

Figure-7.

Figure-7 illustrates the loss curves versus epoch for different training models. Even with all three models having an equal number of units in the hidden layer, LSTM shows the highest loss, measured by Mean Absolute Error (MAE), followed by GRU with a moderately lower loss than LSTM. Notably, our proposed model, ABiGRU, achieves the lowest loss compared to all other training models.

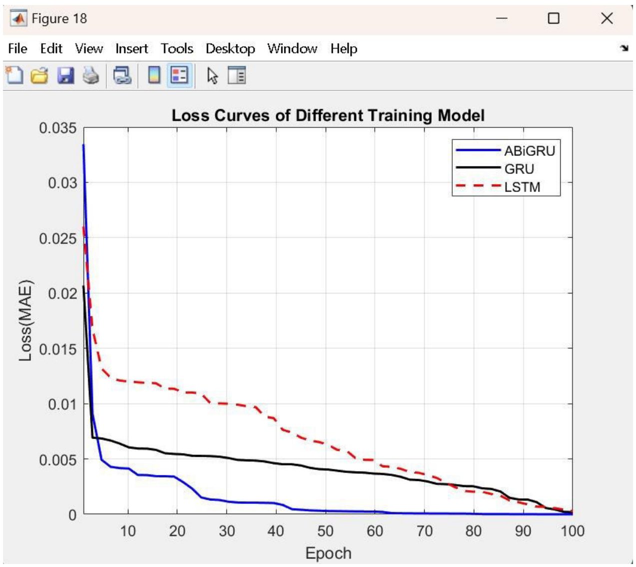

Figure-8.

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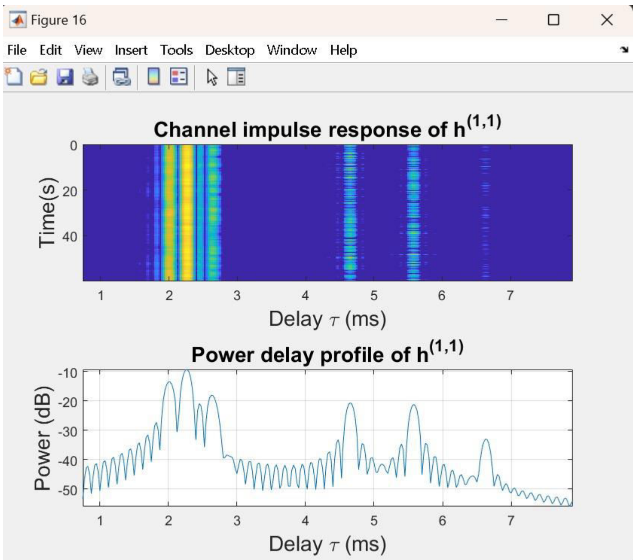
The statistical model developed for characterizing underwater acoustic (UWA) channels is a sophisticated framework that accounts for various physical phenomena and environmental factors influencing communication in underwater environments. These channels are inherently complex, with characteristics that evolve dynamically over time due to factors such as water depth, temperature, salinity, and underwater terrain.

The model incorporates a path loss model to estimate the attenuation of signal strength as it propagates through water, considering factors like distance traveled and frequency of the transmitted signal. Additionally, Rayleigh fading is integrated to simulate the random fluctuations in signal strength caused by multipath propagation, where signals take multiple paths to reach the receiver due to reflections and scattering from underwater surfaces and objects.

Small-scale effects, such as scattering and Doppler shifting induced by the motion of underwater objects or vehicles, contribute to rapid variations in the received signal's strength and phase. On the other hand, large-scale effects encompass changes in environmental conditions over larger spatial scales, such as variations in water temperature and salinity, which can affect the overall propagation characteristics of the channel.

By combining these models, researchers gain a comprehensive understanding of the intricate behavior of UWA channels, allowing for the development of communication systems that are more robust and reliable in underwater environments. Figure-8 provides visual insights into the simulated Channel Impulse Responses (CIRs), showing how the characteristics of the channel change over time, which is crucial for designing effective communication protocols and signal processing algorithms tailored to underwater applications.



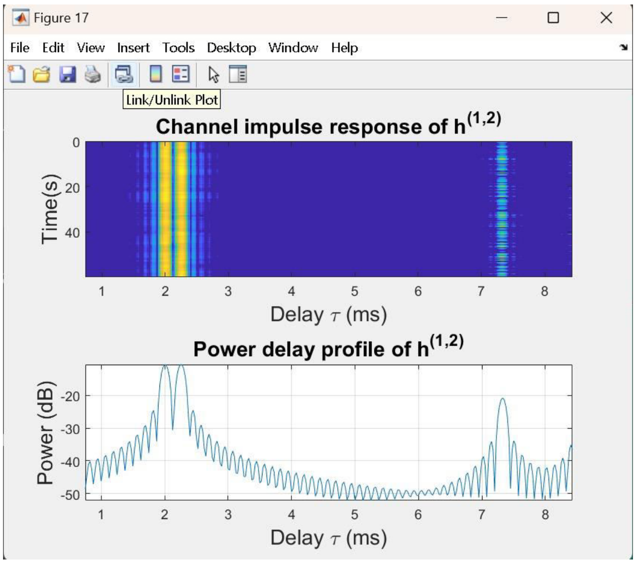
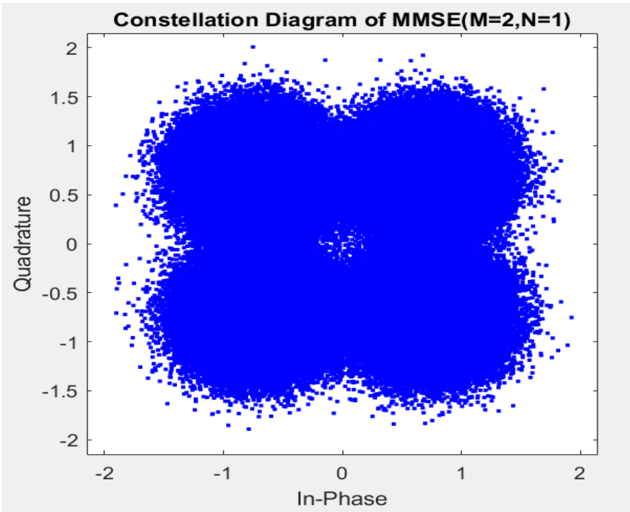
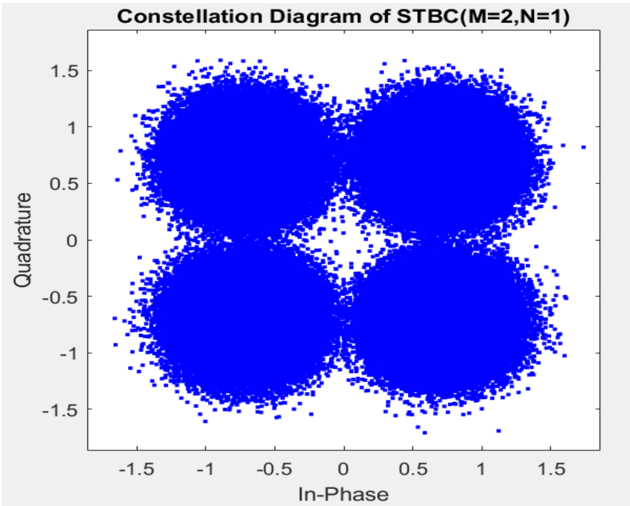


Figure-9.





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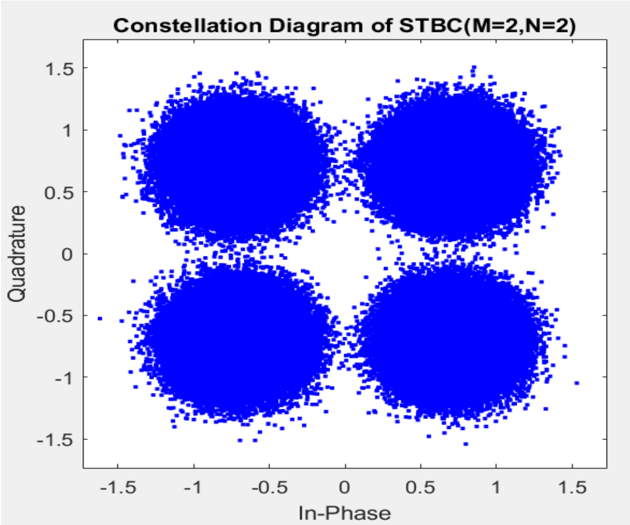

In Figure 9, we observe scattered plots comparing constellation diagrams derived from different pre-equalization methods. These methods include the MMSE pre-equalization method with M = 2, N = 1, the STBC-MMSE pre-equalization scheme with M = 2, N = 1, and the STBC-MMSE pre-equalization scheme with M = 2, N = 2. Each plot divides symbols into four distinct regions across all schemes, reflecting variations in the received signal's quality and integrity.

Interestingly, the STBC-MMSE pre-equalization scheme outperforms the MMSE pre-equalization scheme, showcasing superior symbol recovery quality. Specifically, symbols obtained using the STBC-MMSE pre-equalization scheme exhibit fewer errors and more distinct constellations, indicating enhanced reliability and robustness in symbol transmission. Notably, the STBC-MMSE pre-equalization scheme with M = 2, N = 2 demonstrates the most promising performance among the evaluated schemes, characterized by the fewest error symbols and maximally separated constellations. These findings underscore the effectiveness of the STBC-MMSE pre-equalization scheme, particularly when configured with multiple antennas at both the transmitter and receiver ends, in mitigating channel impairments and optimizing symbol recovery in practical communication scenarios.

CONCLUSIONS

In this paper, we introduce a novel and cost-efficient online channel predictor designed for time-varying Underwater Acoustic (UWA) Multiple-Input Multiple-Output (MIMO) channels. Our proposed ABiGRU model achieves precise real-time predictions of Channel Impulse Responses (CIRs) by utilizing preceding CIRs obtained from channel estimation for online training. Subsequently, the trained model is deployed for CIR prediction, effectively tracking time-varying channels in the operational ABiGRU network. Furthermore, we validate our proposed model through realistic in-field UWA MIMO communication experiments and numerical simulations, demonstrating its practicality and consistency. Additionally, we compare the performance of the ABiGRU network with other algorithms/networks such as adaptive Minimum Mean Square Error (MMSE), Long Short-Term Memory (LSTM), and Gated Recurrent Unit (GRU). Our proposed ABiGRU network exhibits the lowest Mean Squared Error (MSE) value with rapid convergence across different prediction indexes. Moreover, analysis of channel measurement data indicates that the ABiGRU model outperforms MMSE, LSTM, and GRU in terms of average MSE and Bit Error Rate (BER). Future work will focus on developing Recurrent Neural Network (RNN) models for underwater collaborative communications and positioning, exploring UWA MIMO-Orthogonal Frequency Division Multiplexing (OFDM) systems, and optimizing design considerations regarding complexity and performance.

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