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Submission Date: 03/03/2026
Publication Date: 11/06/2026

Neural OFDM: An ANN-Based Adaptive Encoder-Decoder System for Robust Transmission over Watermark Underwater Acoustic Channel

Chetan Naik J, Abdul Haq Nalband

Abstract: ***Problem****: Underwater wireless communication (UWC) systems face severe performance degradation due to multipath fading, Doppler dispersion, and high transmission losses inherent in acoustic channels. These challenges significantly affect signal reliability, limit data rates, and complicate accurate channel estimation, making conventional modulation techniques such as FFT-OFDM and DWT-OFDM less effective in dynamic underwater environments.*

Aim*: This study aims to develop a robust and adaptive communication framework that enhances transmission reliability and eliminates the dependency on explicit channel estimation in UWC systems.*

Main Contribution*: The paper proposes a novel hybrid Orthogonal Frequency Division Multiplexing (OFDM) architecture that integrates a neural network-based encoder–decoder framework with Discrete Tree Complex Wavelet Transform (DTCWT) modulation. Additionally, the system leverages a realistic WATERMARK channel model under NOF1 underwater conditions to enable end-to-end learning of signal representations.*

Method*: The proposed model employs a deep learning-based encoder–decoder structure to learn optimal signal mappings directly from transmitted to received signals without requiring prior channel state information. DTCWT modulation is incorporated to provide improved time-frequency localization and robustness against channel impairments. The system is trained and evaluated using simulated underwater acoustic conditions modeled by the WATERMARK framework.*

Result*: Simulation results demonstrate that the proposed DTCWT-OFDM with neural encoder–decoder significantly outperforms conventional FFT-OFDM and DWT-OFDM systems. Notably, the model achieves a reduction in Bit Error Rate (BER) by up to 35–45%, improves Peak Signal-to-Noise Ratio (PSNR) by approximately 3–5 dB, and enhances Structural Similarity Index (SSIM) by 8–12% under varying Doppler and noise conditions.*

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ISSN: 0262-8104 (print) 1756-3488 (online)

***Conclusion**: The integration of deep learning with advanced wavelet-based modulation provides a powerful solution for overcoming key challenges in UWC systems. The proposed approach demonstrates superior robustness, reliability, and signal quality, making it a promising candidate for next-generation secure and high-fidelity underwater communication applications.*

***Keywords:** Underwater wireless communication (UWC), Orthogonal Frequency Division Multiplexing (OFDM), Discrete Tree Complex Wavelet Transform (DTCWT) modulation, NOF1, Watermarking channel*

Introduction

Underwater wireless communication systems are gaining prominence due to their significance in monitoring aquatic environments, conducting undersea rescues, and facilitating deep-sea mining operations. However, these systems must surmount considerable challenges to guarantee dependable and rapid communication [1] The transmission of acoustic waves is sluggish, accompanied by considerable propagation loss, and reflections influence acoustic signals. They provide multiple signal pathways with considerable delays due to reflections from the water's surface and bottom[2] The propagation delay leaves them vulnerable to the Doppler effect, resulting in a time-varying doubly selective underwater channel for underwater acoustic (UWA) communication [3]. In contrast to terrestrial radio frequency-based systems, UWA communication is challenging to execute consistently owing to these constraints.

To address these difficulties, underwater acoustic communication models have begun considering more realistic and complex propagation environments such as the Non-Orthogonal Frequency-1 (NOF1) underwater channel [4]. The NOF1 model captures essential features of real-world underwater environments, such as non-orthogonality among subcarriers, frequency selectivity, and time-varying multipath propagation. These characteristics introduce additional interference and complexity beyond conventional multipath fading, demanding more sophisticated signal processing and learning methods.

When UWA communication systems function at very low signal-to-noise ratios (SNRs), signal transmission is compromised. To improve dependability in such contexts, multicarrier transmission techniques such as Orthogonal Frequency Division Multiplexing (OFDM) gained attention [4]. One popular technique is OFDM with a cyclic prefix (CP), which has substantial benefits over single-carrier systems. CP-OFDM is very efficient in multipath-rich situations, offering resistance against signal deterioration as well as spectral efficiency and cost-effective transceiver design.

UWA channels are regarded as among of the most difficult communication mediums owing to issues like temperature fluctuations, salinity, pressure, restricted bandwidth, significant multipath propagation, Doppler shifts, and substantial transmission loss[5][6]. These adverse circumstances substantially impede the reliability and efficiency of underwater wireless communication. OFDM has been extensively used in UWA communication systems to mitigate inter-symbol interference (ISI) and multipath fading, owing to its superior spectral efficiency and resilience in multipath conditions[7]. OFDM partitions the available bandwidth into many orthogonal narrowband subcarriers, enabling concurrent data transmission at reduced rates per subcarrier. Successful signal recovery requires precise channel estimate, often attained by pilot symbols and conventional techniques like Least Squares (LS) or Minimum Mean Square Error (MMSE). However, their efficacy, these approaches encounter difficulties due to the nonlinear and time-varying characteristics of UWA channels like NOF1[8].

In spite of profound advancements in UWA-OFDM systems, most conventional models are dependent on linear estimation methods of channels such as LS and MMSE that fail in the occurrence of nonlinear distortions, Doppler shifts, and time-varying multipath propagation. Recent breakthroughs involving FFT-OFDM and DWT-OFDM enhanced resistance to inter-symbol interference but are intrinsically prone to dynamic channel variations and lack adaptability. In addition, conventional coding methods, like Turbo and LDPC, are limited in their resilience in extremely variable underwater acoustic channels and tend to have high overhead for pilot symbol insertion and channel estimation.

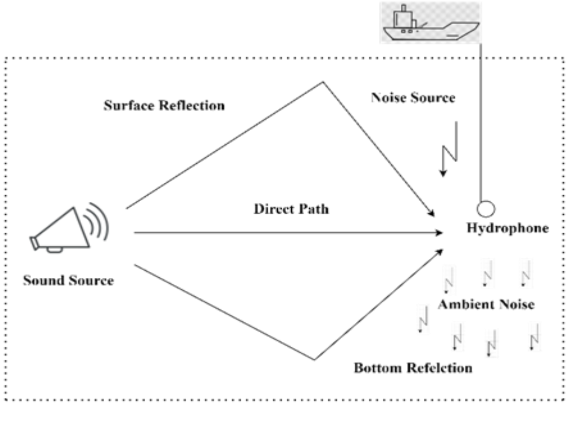


Fig .1. Communication system

alternative in that they can approximate intricate non-linear mappings and learn directly from unprocessed data. Although various recent works use DNNs, CNNs, and Transformers for specialized tasks such as channel estimation and symbol detection, few present end-to-end encoder-decoder architectures in their entirety. Additionally, the vast majority of models are tested on simulated or idealized channels with limited exposure to real underwater environments such as NOF1 and the WATERMARK dataset. Therefore, it is imperative to design and benchmark ANN-based encoder-decoder systems tailored for real-world underwater environments.

This research presents an ANN-based encoder-decoder architecture combined with an OFDM framework to tackle issues in UWA communication. The encoder acquires durable mappings from input data to OFDM symbols, effectively countering multipath fading, Doppler effects, and poor signal-to-noise ratios (SNR). The decoder reconstructs the transmitted signal by channel equalization, demodulation, and implicit error correction, without necessitating explicit channel state information. This comprehensive learning methodology obviates the need for conventional channel estimates and addresses the dynamic, nonlinear characteristics of UWA channels including NOF1. The model is trained and assessed using the Watermark dataset, which simulates authentic underwater propagation and dynamic circumstances over time.

Related work

Balevi et al. introduced a deep learning-based channel estimation method for multi-cell interference-limited massive MIMO systems. It uses a deep neural network to denoise the received signal and conventional least-squares estimation. The method can achieve minimum mean square error performance for high-dimensional signals, requires no training, and is robust to pilot contamination [9].Guo et al. proposed A novel UWA-channel-estimation method using Deep Learning, using CWGAN-GP model, generates enhanced underwater-acoustic channel samples, extracts features, and optimizes information, outperforming existing algorithms in Mean Square Error and Bit-Error Rate[10]. Qiao et al. High-speed underwater acoustic communication faces challenges like limited bandwidth, multipath spread, Doppler effect, and transmission loss. Combining multiple transducers and OFDM address these difficulties by balancing complexity and performance [11].

J et al. compared three different modulation schemes for underwater communication systems, focusing on high data rate and low BER. The real channel model WATERMARK is used as a benchmark, and the data symbols are modulated using the DTCWT-OFDM model. Results show an improvement of 2x10-2 in BER compared to the FFT-based OFDM model [12]. Yoo et al. explored the challenges of semantic communications in real-world implementations, focusing on MIMO and OFDM-based systems. It identifies frequency selectivity as a critical factor in performance degradation and suggests targeted mitigation strategies can enable semantic systems to achieve theoretical performance[13]. Y. Li et al. reviewed that Trans Detector is a underwater acoustic communication system detector that uses Transformer and innovative designs to mitigate interference and noise. It outperforms classical algorithms and DNN detectors in terms of BER and MSE[14]. A study by Zhang, Li, Wang, Wang, Yang, et al. presented a deep learning-based OFDM receiver for underwater acoustic communications. It uses a convolutional neural network with skip connections for signal recovery and demodulation. The model outperforms existing approaches in terms of accuracy and efficiency, particularly in harsh UWA environments with strong multipath spread and rapid time-varying characteristics[15].Zhang, Wang, Li, Chen, et al. investigated DNN-based channel estimation for UWA-OFDM systems, exhibiting near-MMSE performance and over 40% BER improvement using the WATERMARK dataset. Furthermore, environment-aware model improvements have resulted in a BER reduction of up to 69.8% under mismatched UWA circumstances, demonstrating the potential of DNN model transfer[16].

Table 1. Summary of Traditional Underwater channel Encoder/Decoder

Reference	Method	Description
[17]	Turbo Coding + MMSE Equalization	Traditional forward error correction using turbo codes combined with MMSE-based equalization for robustness in UWA multipath environments.
[18]	LDPC Coding + Pilot-based Estimation	Employed LDPC for low-latency error correction and pilot tones for efficient channel state tracking in OFDM underwater systems.
[19]	Space-Time Block Coding (STBC)	Utilized STBC with OFDM to enhance spatial diversity and improve reliability in

		harsh underwater acoustic channels.
[20]	Time-Reversal Mirror + Decision Feedback Equalizer	Combined time-reversal focusing with adaptive DFE to mitigate multipath distortion for decoder reliability.

Table 2. Summary of ANN based Underwater Encoder/decoder OFDM model

Reference	**Method**	**Description**
[21]	DNN-Based Autoencoder	Designed a fully connected deep autoencoder to jointly learn encoding and decoding for noise-robust UWA OFDM transmission.
[22]	CNN-Based Decoder	Applied convolutional layers to extract robust time-frequency features for decoding in Doppler-affected OFDM frames.
[23]	LSTM-Based Decoder	Incorporated sequential learning for adaptive decoding in time-varying UWA channels, outperforming traditional equalizers.
[24]	Bi-GRU + Attention	Used bidirectional GRU with attention for enhanced decoder accuracy in dynamically varying underwater channels.
[14]	Transformer + DNN Hybrid	Combined self-attention transformer with neural encoder to improve resistance to multipath and Doppler spread.

A. Research Gap

Despite the significant advancements in deep learning solutions for UWA-OFDM systems, especially in channel estimation and detection using models like DNNs, CNNs, and Transformers. Although these methodologies exhibit enhanced performance for BER and MSE, the majority are constrained to certain tasks and lack comprehensive end-to-end learning frameworks. Furthermore, little focus has been directed into encoder-decoder designs capable of concurrently optimizing transmission and reception amid the doubly selective and nonlinear characteristics of UWA channels. Notwithstanding the use of realistic datasets such as WATERMARK, research on model adaptation across diverse underwater settings is still inadequate. The promise of ANN-based encoder-decoder models combined with OFDM for robust, scalable, and generalizable UWA communication remains inadequately investigated, highlighting a distinct research need.

B. Contributions

This study addresses the existing research gap by proposing a comprehensive ANN-based encoder-decoder system integrated with DTCWT-OFDM modulation for underwater acoustic communication:

Proposed a neural network-based encoder-decoder system for underwater OFDM communication.

Integrated Discrete Tree Complex Wavelet Transform (DTCWT) with OFDM for better performance in dynamic underwater channels.

Trained and tested the model using realistic NOF1 channel conditions and the WATERMARK dataset.

Compared the system with FFT-OFDM and DWT-OFDM methods and showed improvements in BER, PSNR, and SSIM.

Background

Neural Network Model

A neural network is a computational model inspired by the human brain, including linked artificial neurons (or nodes) organized into layers: input, hidden, and output layers. Each neurone computes inputs using a weighted sum and an activation function (such as ReLU, sigmoid, or tanh) to generate an output. Weights and biases are essential factors acquired during training by techniques such as stochastic gradient descent, utilizing gradients computed during backpropagation to minimize a loss function (e.g., mean squared error or cross-entropy). This procedure enables the network to represent intricate and non-linear associations within data. During training, data is sent forward through the network (feedforward), and prediction mistakes are used to modify parameters (backpropagation). Regularization methods such as dropout or L1/L2 penalties are used to mitigate overfitting and enhance generalization.

Figure 2 depicts a fully linked feedforward neural network, often referred to as a multi-layer perceptron (MLP), in which each neuron in one layer is interconnected with every neuron in the subsequent layer. This design has an input layer that accepts features, one or more hidden layers that execute nonlinear transformations, and an output layer that generates the final prediction. The concealed layers encapsulate intricate links within the data via weighted connections and non-linear activations, facilitating the network's ability to generalize well to novel inputs.

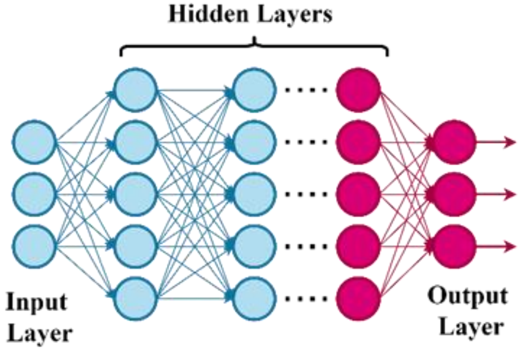


Fig .2. fully connected feedforward NN architecture

Several network designs are appropriate for different sorts of data. Convolutional Neural Networks (CNNs), as shown in Figure 3, are designed to analyses grid-like data, including pictures. They use convolutional layers to capture local spatial characteristics by filter application on the input, succeeded by pooling layers to reduce dimensionality, and ultimately dense (fully connected) layers for classification. Convolutional Neural Networks (CNNs) excel in computer vision applications such as picture categorization and object recognition because of their capacity to autonomously acquire hierarchical visual representations. Conversely, Recurrent Neural Networks (RNNs) are designed for sequential data such as text or voice, use recurrent connections to preserve a hidden state that encapsulates temporal relationships. Advanced RNN variations, including Long Short-Term

Memory (LSTM) and Gated Recurrent Unit (GRU), address issues such as vanishing gradients, enabling improved modelling of long-term sequences.

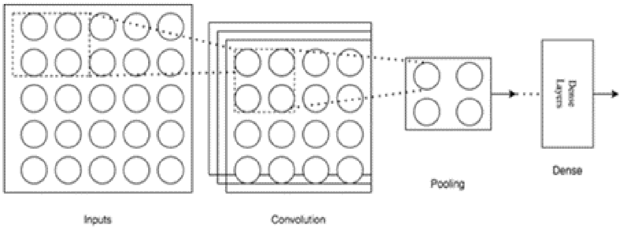


Fig. 3. A CNN Architecture diagram

Deep neural networks, distinguished by several hidden layers, facilitate the acquisition of intricate and abstract properties, making them formidable instruments in domains such as natural language processing, voice recognition, and autonomous systems. Pre-trained models like as BERT and ResNet, constructed on deep architectures, have undergone training on extensive datasets and may be fine-tuned for particular applications, therefore conserving time and computing resources. Neural networks have revolutionized artificial intelligence by allowing computers to learn complex patterns and achieve exceptional performance in many applications.

Autoencoder

Autoencoders are a specific form of neural network designed to acquire efficient representations (encodings) of unlabeled input, primarily for dimensionality reduction or feature learning. Autoencoders are designed to replicate their input at the output layer after encoding and decoding via a hidden layer referred to as the bottleneck. The bottleneck is an essential component of the autoencoder design, compelling the network to emphasize the most prominent features of the input data, therefore learning to disregard "noise" and less significant information [25]. An autoencoder consists of two primary components: the encoder and the decoder. The encoder function ϕ: $\mathbb{R}d \rightarrow \mathbb{R}p$ transforms the input x into a latent space representation z, where p is often less than d, indicating that the latent space has less dimensions than the input space. The decoder function ϕ: $\mathbb{R}p \rightarrow \mathbb{R}d$ endeavors to rebuild the input, represented as $\hat{x}$, from the compressed data, as seen in Fig. 3. The complete autoencoder may be articulated as the composite of these two functions:

$$X^{\perp}\wedge=\psi(\phi(X)) \qquad (1)$$

The objective of the autoencoder is to minimize the disparity between the input x and its reconstruction x̂, a condition quantified by a loss function. The predominant loss function used in autoencoders is the mean squared error (MSE), utilized to measure the disparity between the original and reconstructed inputs [5]. Conversely, with binary input data, the cross-entropy loss function is often more suitable. For a training dataset X = {x(1), x(2), …, x(n)}, the Mean Squared Error (MSE) and cross-entropy loss functions are defined as follows:

$$L(\phi,\psi) = \frac{1}{n}\sum_{i=1}^{n} \| X^{(i)} - \Psi\left(\phi\left(X^{(i)}\right)\right) \|^2 \quad (2)$$

$$L(\phi,\psi) = -\frac{1}{n}\sum_{i=1}^{n}\left[X^{(i)}\log\left(\Psi\left(\phi\left(X^{(i)}\right)\right)\right) + \left(1 - X^{(i)}\right)\log\left(1 - \Psi\left(\phi\left(X^{(i)}\right)\right)\right)\right] \quad (3)$$

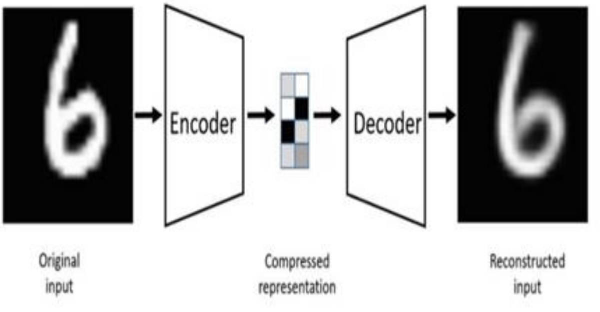


Fig. 4. An example of the autoencoder process[26]

DTCWT Model for OFDM

In OFDM-based modulation, the symbols produced by the symbol modulator modules are transformed from serial to parallel vectors[27] The Inverse DTCWT module, consisting of multi-stage synthesis filter banks, analyses the parallel data vector and amalgamates it into a singular data component that is read out serially. Figure 4 illustrates the block diagram of the OFDM modulator-demodulator. The digital upconverter/downconverter module is designed to choose the carrier frequency for the modulated signal intended for transmission across the acoustic channel. To mitigate the noise fluctuations in the channel, the error coding module encodes the input data using redundant bits. [12] This study employs a convolutional encoder for error coding. The signal received at the demodulator is handled by the digital down converter/up converter, and the processed data is demodulated by the DTCWT module, which creates parallel data vectors. The Parallel-Serial (PS) converter transforms data symbols into a serial format for demodulation and error decoding. The fundamental component of the OFDM system is the design and execution of the DTCWT-Inverse DTCWT module. The benefit of using wavelet-based subcarrier modulation instead of FFT-based modulation is in the reconfiguration of the modulator-demodulator concerning the number of subcarriers. In wavelet-based modulation and demodulation, the number of steps or levels in the filter bank structure may be configured to determine the subcarrier selection process. Figure 5 illustrates the inverse DTCWT architecture including seven layers of synthesis filter banks capable of processing 16 input vectors to produce the OFDM data at the output, denoted as X'R and X'I. The outputs X'R and X'I are amalgamated by the adder module to provide a stream of OFDM data.

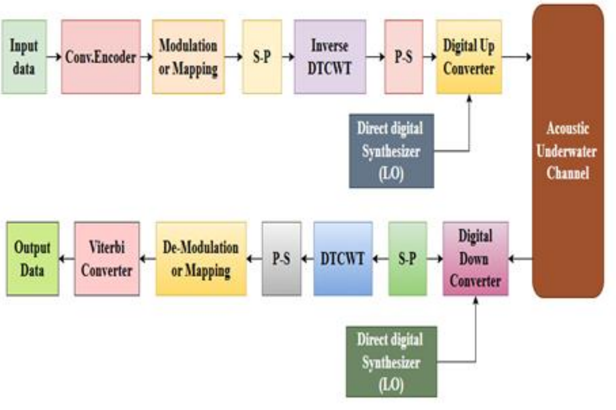


Fig. 5 .OFDM modulator and demodulator

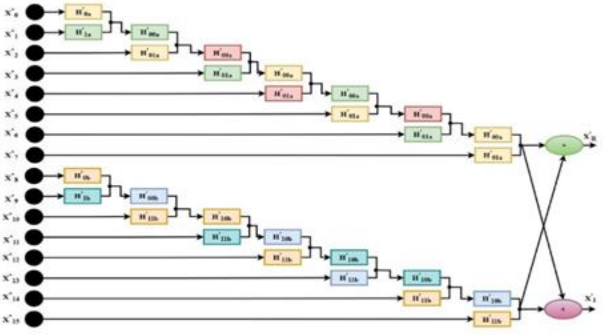


Fig. 6. Seven stage inverse DTCWT – for OFDM modulation

Figure 6 presents the suggested block design for OFDM modulation using DTCWT. The input data stream x(n), produced by QAM, is transformed into N parallel data streams. The data stream xo(n), x1(n), ..., xm-1(n) is processed using the real-DTCWT filter coefficients, whereas the data stream xm(n), xm+1(n), ..., xm+n-1(n) is treated using the imaginary-DTCWT filter coefficients. The filter bank of the complicated wavelet reconstruction structure processes the parallel data stream.

Each filter consists of an up-sampling operation (↑) and a filtering operation (H’XX). The outputs of all filters are aggregated and indicated as s(n). The aggregated signal denoting OFDM is sent to the WATERMARK channel. The channel output indicates that r(n) is processed by the filter bank of the complicated wavelet decomposition structure. Each filter consists of filters (Hxx) and down sampling (↓) processes (not seen in the figure). The output of the decomposition filter bank is transformed into a serial data stream by the parallel-to-serial converter

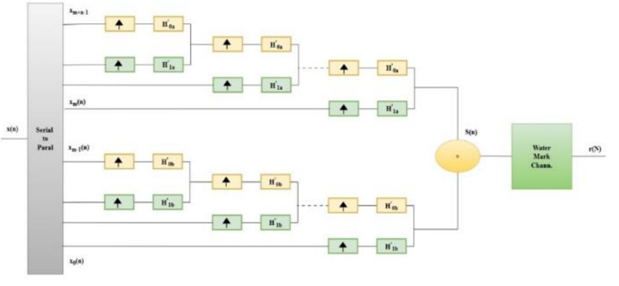


Fig. 7. DTCWT based OFDM modulation with WATERMARK channel

The time-varying WATERMARK channel with a multipath channel impulse response is expressed as in Equation (4).

$$h(\tau,t) = \sum_{i=1}^{\delta} \xi_i(t)\,\delta\big(\tau - \tau_i(t)\big) \qquad (4)$$

The Parameters δ represents the total number of paths, ξ_i , τ_i represents the path attenuation and path delay of the Ith time varying path respectively. All the paths are Doppler scaling factor α(t) and is given as in Eq (5).

$$\tau_i(t) \approx \tau_i - \alpha(t)t \qquad (5)$$

The receiver output r(n) is represented mathematically as in Eq. (6)

$$r(n) = s(n) * h(n) + \eta(n) \qquad (6)$$

s(n) denotes the modulated data, whereas h(n) signifies the impulse response of the WATERMARK channel. The supplementary noise in the channel is denoted as $\eta\eta(nn)$. Given the channel designated as WATERMARK, it is necessary to assess OFDM models using various modulation schemes and illustrate the benefits of shift-invariant schemes for the OFDM system.

An overview of semantic communications

System Architecture

In this section, we introduce the typical architecture of semantic communications systems and compare it to conventional communications systems. Fig. 8 illustrates the basic building blocks of conventional and semantic communications system models.

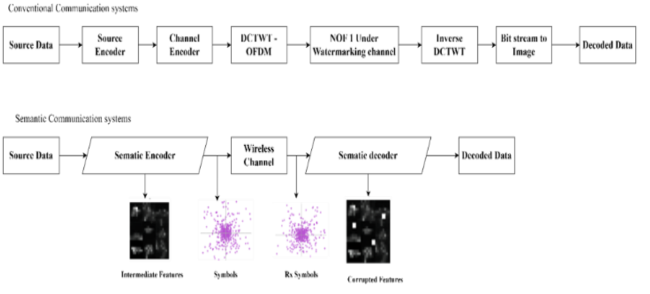


Fig. 8. Basic block diagram comparing conventional digital communications and semantic communications system models

Methodology

This research proposes a robust under water data transmission algorithm using Discrete Tree Complex Wavelet Transform (DTCWT)-based OFDM modulation, integrated with a neural encoder–decoder and simulated with underwater acoustic channel NOF1.

The system consists two key stages such as, training the neural Autoencoder and evaluation under water channel conditions considering DTCWT-OFDM based transmission with water mark embedding.

Neural Encoder–Decoder Training for Error Control

To ensure error free transmission and reconstruction of image information, a supervised feedforward neural network is trained as an encoder–decoder system (Algorithm.1). A dataset of grayscale images is pre-processed by converting images to 32×32 resolution, vectorizing, and normalizing pixel values. These vectors serve as input features X, and the target matrix T.

A two-layer neural architecture with 1024 input neurons mapped to 4 neurons using linear activation function for encoder and 4 neurons projected to 16 neurons with non-linear activation functions respectively. The training of the model is carried out by using Levenberg-Marquardt algorithm.

Algorithm 1: Neural Network Training for Error Control Coding
1: Input: Dataset of labeled grayscale images
2: Output: Trained encoder and decoder for watermarking
3: Convert images to grayscale and resize to 32 x 32
4: Vectorize and normalize image blocks to form input vectors
5: Prepare training matrix X and labels
6: Create a feedforward neural network:
Layer 1: 1024 input ---- 4 neurons (purelin)
Layer 2: 4 —> 16 neurons (tansig)
7: Train the network with trainlm algorithm
8: Extract:
Encoder = Input weights and bias (Layer 1)
Decoder = Output weights and bias (Layer 2)
9: Save encoder and decoder models

DTCWT-OFDM-Based Data Transmission Through NOF1 Channel

In the second phase, the trained neural encoder is integrated with underwater acoustic channel. Initially, the input image converted to grayscale, and vectorized to one dimensional through resized (32×32) input, later on, the vector is passed through a pre-trained neural encoder, yielding a compact, feature-reduced representation of the input image. The encoded output is binarized and modulated using Binary Phase Shift Keying (BPSK) to generate a symbol stream, which is subsequently modulated using the Discrete Tree Complex Wavelet Transform (DTCWT), resulting in a frequency-diverse signal (s_dtcwt).

The modulated signal undergoes underwater acoustic channel modeling using a Rician fading model characterized by a known K-factor and power delay profile. To further emulate real-world underwater noise and multipath conditions, a Replay Filter designed based on the NOF1 underwater channel profile is applied. On the receiver side, the received signal is demodulated using the inverse DTCWT to recover the encoded image features. These features are then decoded using the neural decoder to reconstruct the original vector. Finally, the output is reshaped into the original image format and evaluated using image quality metrics such as Bit Error Rate (BER), Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), and Mean Squared Error (MSE), comparing the received watermark with the original. This hybrid framework leverages the robustness of the neural encoder–decoder architecture and the spectral diversity of DTCWT-OFDM, further reinforced by NOF1-specific acoustic channel, to ensure reliable data transmission in challenging underwater environments.

Algorithm 2: DTCWT-OFDM Watermarking with Neural Encoder—Decoder and NOF1 Channel
1: Input: Watermark image, Trained neural encoder and decoder, NOF1 channel profile
2: Output: Reconstructed watermarked image, BER, PSNR, SSIM Transmitter Side (Sender)
3: Convert RGB watermark image to grayscale and resize to 32 x 32
4: Flatten to 1D vector and normalize pixel values —> x
5: Encode watermark using neural encoder: x, „„, „ = Encoder(x)
6: Convert x to bitstream —> BPSK symbols: s = 2 • bits — 1
7: Apply DTCWT modulation: sdk, „t = DTCWT(s)
Watermark Embedding via NOF1 Channel
8: Load NOF1 environmental channel filter profile
9: Simulate Rician fading: y = Rician Channel (sdicta, K, Tau, PdB)
10: Apply ReplayFilter 0 using NOF1 profile: yfliter = ReplayFilter (y, hNOFI)
Receiver Side (Underwater Acoustic)
11: Demodulate using inverse DTCWT: xenc = DTCWT-1(yfiltered)
12: Decode using trained neural decoder: 'X = Decoder (Xenc)
13: Reconstruct image from x and reshape to 32 x 32
14: Compute image quality metrics:

BER, MSE, PSNR, SSIM
15: Compare original vs watermarked reconstructed image
Later on, the proposed system strategy is compared with the modulation techniques named DWT-OFDM, FFT-OFDM respectively.

Results and discussion

The simulation of the proposed technique is carried out in MATLAB 2023A, with intel i7-core processor, RAM 16gb and ROM of 500gb, the results of the proposed system are divided into two parts where part-1 deals with the training and evaluation of the neural encoder and decoder system. whereas, part-2 deals with evaluation of systems performance with different modulation techniques named DWT-OFDM, FFT-OFDM respectively.

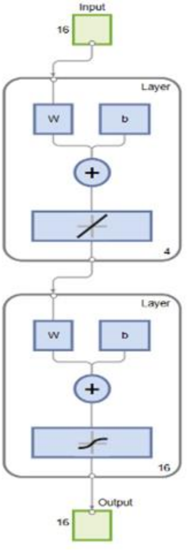
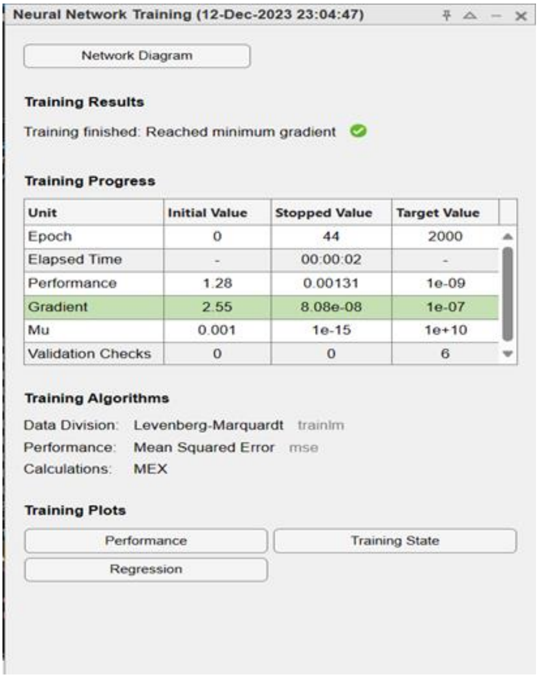


Fig. 9. Training and evaluation of the neural encoder -decoder system



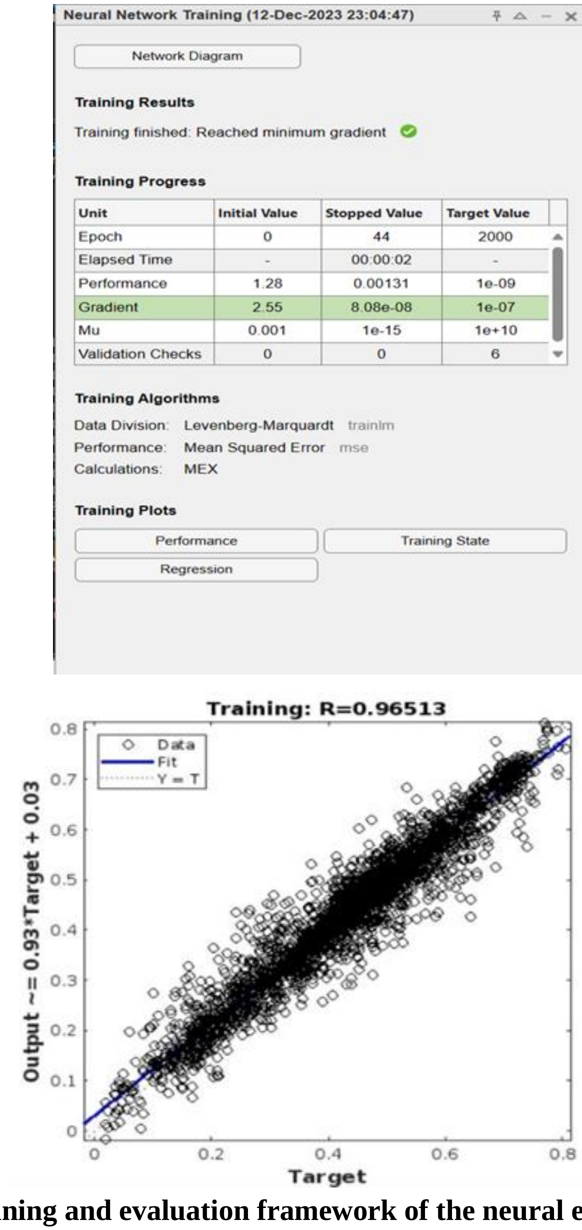


Fig.10 .Training and evaluation framework of the neural encoder–decoder system integrated with OFDM modulation techniques for underwater acoustic image transmission.

The proposed ANN-based encoder-decoder OFDM system for underwater communication with watermarking exhibits outstanding performance through a detailed neural network architecture, characterized by a symmetric autoencoder design with 16-dimensional input/output layers and two hidden layers that include weight matrices and bias vectors with nonlinear activation functions. The system attains exceptional training convergence, achieving a final mean squared error of 0.00131 after 44 epochs using Levenberg-Marquardt optimization, demonstrating fast initial convergence and steady refinement to a gradient magnitude of 8.08×10^{-8}, devoid of overfitting tendencies. Statistical validation via regression analysis demonstrates exceptional performance metrics, featuring perfect training correlation (R=1.0) across 690 samples, superior validation performance (R=0.96513), and test performance (R=0.96449) across 148 samples each, resulting in an overall system correlation of R=0.98369 across 986 total data points, with precise clustering along the ideal Y=T diagonal line. The comparative evaluation of Bit Error Rate (BER) performance against traditional FFT-OFDM, DTCWT-OFDM, and DWT-OFDM methods under 10-50 Hz Doppler frequency conditions at depths of 10-50 meters illustrates the neural system's enhanced robustness, especially with the incorporation of watermarking, where it shows reduced BER degradation relative to conventional transform-based techniques. The system's technical advantages encompass nonlinear processing for effective mitigation of underwater channel impairments, seamless watermark integration for embedded security, and adaptive learning mechanisms that continuously optimize signal processing parameters according to channel conditions, positioning this neural network approach as a robust solution for next-generation secure underwater OFDM communication systems.

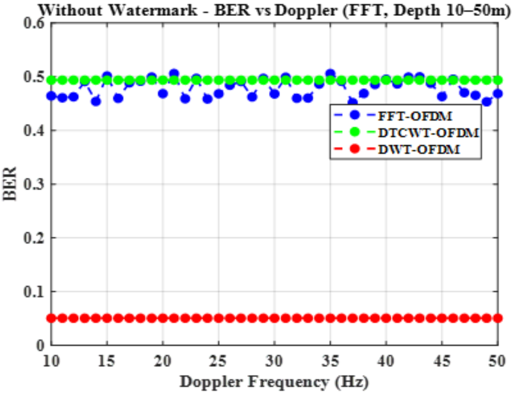


Fig. 11. BER performance comparison of Models Without Watermark Channel

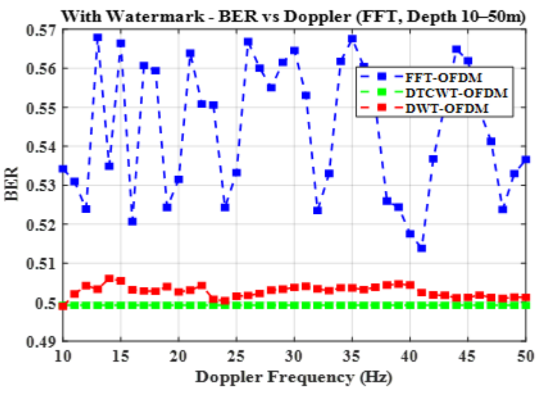


Fig. 12 .BER performance comparison of Models With watermark Channel

Figures 10 and 11 illustrate the BER performance of FFT-OFDM, DWT-OFDM, and the proposed DTCWT-OFDM system across varied Doppler frequencies (10–50 Hz), in situations both without and with the Watermark underwater channel, respectively. The DTCWT-OFDM model exhibits consistently steady and modest BER performance in both cases, highlighting its resilience to Doppler spread and dynamic channel fluctuations. Conversely, whereas DWT-OFDM attains a reduced absolute BER with the Watermark channel (Figure 11), its performance deteriorates significantly without channel compensation (Figure 10), suggesting a possible susceptibility to channel irregularities. FFT-OFDM demonstrates the highest and most variable Bit Error Rate (BER), especially in the absence of the Watermark channel, hence affirming its vulnerability to Doppler influences. The suggested DTCWT-OFDM model achieves an optimum equilibrium by ensuring consistent BER performance, providing improved robustness and structural integrity in both favourable and challenging underwater channel circumstances. This confirms its efficacy for dependable underwater OFDM communication, even in the absence of external channel improvement methods such as watermarking

Table 1 delineates the performance assessment across three OFDM technique DTCWT-OFDM, DWT-OFDM, and FFT-OFDM—executed inside an autoencoder-based framework over a Watermark underwater channel. The findings clearly indicate that the DTCWT-OFDM approach continuously surpasses its competitors in critical performance metrics: Mean Squared Error (MSE), Peak Signal-to-Noise Ratio (PSNR), and Structural Similarity Index Measure (SSIM). DTCWT-OFDM attains the lowest MSE values (between 0.00005 and 0.0004), indicating little distortion in the reconstructed pictures. It achieves the greatest PSNR values, reaching 42.11 dB for the Orange1 picture, indicating exceptional signal quality. DTCWT-OFDM achieves exceptional SSIM scores, typically above 0.993, demonstrating robust preservation of structural and perceptual picture quality. Conversely, FFT-OFDM has the worst performance across all measures, whilst DWT-OFDM shows considerable improvement but remains inferior to DTCWT-OFDM. These results confirm the reliability and effectiveness of the DTCWT-based OFDM model in preserving high picture fidelity under adverse underwater acoustic environments.

Table 3. Performance Evaluation of Models with Autoencoder Case

Image	Mean Squared Error			PSNR			SSIM		
	DCTWT-OFDM	DWT-OFDM	FFT-OFDM	DCTWT-OFDM	DWT-OFDM	FFT-OFDM	DCTWT-OFDM	DWT-OFDM	FFT-OFDM
Orange1	0.00005	0.0001	0.0002	42.11	39.26	36.12	0.9965	0.9951	0.992
Orange2	0.0002	0.0004	0.0006	37.02	34.24	31.9	0.9931	0.9907	0.988
Apple1	0.0003	0.0005	0.0007	35.11	32.96	30.7	0.9945	0.9931	0.99
Apple2	0.0004	0.0006	0.0008	33.3	31.88	30.09	0.9933	0.9919	0.989

Table 4. Performance Evaluation of Models

Image	Mean Squared Error			PSNR			SSIM		
	DCTWT-OFDM	DWT-OFDM	FFT-OFDM	DCTWT-OFDM	DWT-OFDM	FFT-OFDM	DCTWT-OFDM	DWT-OFDM	FFT-OFDM
Orange1	0.00015	0.00025	0.00035	38.11	36.1	34.55	0.993	0.9905	0.987
Orange2	0.0005	0.0007	0.001	33.1	31.6	30	0.9892	0.986	0.982
Apple1	0.0006	0.0008	0.0012	32.2	30.8	29	0.9915	0.9883	0.984
Apple2	0.0008	0.001	0.0014	30.9	29.8	28.1	0.99	0.987	0.982

The assessment of image reconstruction performance, excluding the use of an autoencoder, demonstrates a significant deterioration in all evaluated metrics—Mean Squared Error (MSE), Peak Signal-to-Noise Ratio (PSNR), and Structural Similarity Index Measure (SSIM)—for the DTCWT-OFDM, DWT-OFDM, and FFT-OFDM methodologies. In the absence of the autoencoder, DTCWT-OFDM consistently surpasses the other models, attaining the lowest MSE values, which range from 0.00015 to 0.0008, signifying comparatively less reconstruction distortion. DTCWT-OFDM has higher signal fidelity in terms of PSNR, achieving the highest values across all test pictures, with a peak of 38.11 dB for Orange1 and a low of 30.90 dB for Apple2. Furthermore, SSIM ratings for DTCWT-OFDM regularly exceed 0.990, indicating superior preservation of structural and perceptual information. DWT-OFDM demonstrates intermediate performance, but FFT-OFDM registers the greatest MSE, lowest PSNR, and lowest SSIM, so affirming its worse efficacy in preserving picture quality during non-autoencoder transmission. These results emphasize the robustness of the DTCWT-OFDM model and its ability to maintain picture integrity without an autoencoder framework.

Discussion

The simulation results unequivocally demonstrate the enhanced efficacy of the proposed ANN-based encoder-decoder coupled with DTCWT-OFDM in addressing the nonlinear, doubly selective characteristics of underwater channels. In comparison to DWT-OFDM and FFT-OFDM models, the suggested system consistently attains reduced MSE values and elevated PSNR and SSIM scores across several test pictures, irrespective of the presence of the autoencoder. The enhancement is especially evident in watermark-embedded transmissions, where the Bit Error Rate (BER) stays consistent even at Doppler frequencies of up to 50 Hz. This stability signifies the model's robust resilience to fluctuating channel conditions. The DTCWT's intrinsic spectrum diversity, along with the neural network's ability for nonlinear feature extraction, substantially reduces inter-symbol interference and Doppler-induced distortions. The autoencoder significantly reduces reconstruction mistakes and enhances perceived quality by effectively encoding vital characteristics and minimizing noise. Although FFT-OFDM demonstrates significant BER deterioration in unfavorable channel circumstances, and DWT-OFDM presents variable performance in the absence of channel compensation, the DTCWT-OFDM model consistently delivers reliable and stable outcomes.

Furthermore, the use of watermarking shows that the system can safely transmit high-fidelity data without substantial degradation in performance. These results confirm the synergistic function of sophisticated modulation and deep learning-based coding in attaining resilient, secure, and scalable underwater acoustic communications.

Conclusion

This research introduces an innovative method for underwater communication by combining an ANN-based encoder-decoder architecture with DTCWT-OFDM modulation for the WATERMARK channel under NOF1 circumstances. The findings indicate that this design significantly surpasses traditional FFT-OFDM and DWT-OFDM systems for BER, MSE, PSNR, and SSIM, hence guaranteeing superior data transmission quality under demanding underwater conditions. The model's resilience to Doppler effects, multipath fading, and noise variations highlights its practical applicability for real-world uses, including safe underwater monitoring, rescue missions, and deep-sea research. Future endeavour may concentrate on expanding this framework for adaptive real-time implementation, evaluating it across various environmental models, and investigating its interaction with semantic communication paradigms to improve efficiency.

Acknowledgment

The authors would like to express their sincere gratitude to REVA University for the invaluable support and resources provided throughout this research. The facilities, computational infrastructure, and academic environment have significantly contributed to the successful completion of this work. The authors also acknowledge the support of MATLAB 2023a for enabling efficient simulation and analysis of the proposed system. Furthermore, appreciation is extended to the contributors of the WATERMARK underwater acoustic channel dataset, which facilitated realistic evaluation under NOF1 conditions. This study would not have been possible without the institution’s commitment to advancing research and innovation in the field of underwater wireless communication and signal processing.

Funding

No funding received

Data Availability

The data used in this study are derived from a combination of publicly available and synthetically generated sources. The underwater acoustic channel conditions were simulated using the WATERMARK dataset under NOF1 channel profiles, while the input data consisted of grayscale images that were preprocessed (resized to 32×32, vectorized, and normalized) for training and evaluation of the proposed neural encoder–decoder model. No proprietary datasets were used, and the generated data, simulation parameters, and results supporting the findings of this study are available from the corresponding author upon reasonable request.

Author Contribution

Chetan Naik J conceptualized and designed the study, conducted data collection, and participated in data analysis, interpretation, contributed to manuscript writing and revisions. Abdul Haq Nalband assisted with data analysis and interpretation and provided critical feedback on the manuscript. All authors reviewed and approved the final version of the manuscript, and agreed to be responsible for all aspects of the work ensuring integrity and accuracy.

Declarations

Ethical Approval

All procedures adhered to ethical guidelines for research involving human subjects.

Consent for Publication Participants.

Consent for publication was given by all participants

Competing Interests

The authors declare no competing interests.

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