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Free Space Optical Turbulent Channel Estimation based on the Deep Combined CNN And Bilstm Network

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Abstract:

Free Space Optical (FSO) communication systems are highly susceptible to atmospheric turbulence, which significantly impacts channel state estimation and system performance. Traditional channel estimation methods, such as Least Squares (LS), Linear Minimum Mean Square Error (LMMSE), and Extended Kalman Filter (EKF), often fail to handle the non-linear characteristics of channels under varying turbulence conditions. This paper introduces a novel deep learning-based channel estimation method combining Convolutional Neural Networks (CNN) and Bidirectional Long Short-Term Memory Networks (BiLSTM), trained to predict Channel State Information (CSI) for Gamma-Gamma distributed FSO channels. Simulations are conducted under weak, moderate, and strong turbulence, demonstrating that the proposed method significantly outperforms classical approaches in terms of normalized mean square error (NMSE) and bit error rate (BER). The results show that the proposed method achieves robust performance, especially under strong turbulence, with lower computational complexity compared to iterative methods like EKF.

Keywords: Channel Estimation, BiLSTM, Free Space Optical, Channel State Information.

1- Introduction

Channel estimation in free-space optical (FSO) communication systems is a critical aspect due to challenges such as atmospheric turbulence and pointing errors. Various studies have employed both classical methods and advanced machine learning approaches to enhance the system's performance. In [1], the authors analyzed a MIMO system under gamma-gamma turbulence, considering pointing errors, and demonstrated the suitability of the gamma-gamma distribution for modeling atmospheric turbulence. In [2], the performance of all-optical amplify-and-forward relaying over log-normal FSO channels was investigated, highlighting the robustness of the log-normal model under moderate turbulence conditions. In [3], the performance of a MIMO-FSO system under log-normal distribution was studied, emphasizing its efficiency under specific turbulence scenarios. Deep learning has emerged as a powerful tool for channel estimation in FSO systems. In [4], an introduction to the application of deep learning in physical layer communications was presented, providing the basis for its application

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in channel estimation. In [5], the power of deep learning for channel estimation and signal detection in OFDM systems was demonstrated, illustrating the potential for adaptation in FSO systems. In [6], the effectiveness of deep learning models for physical layer communications was further validated, showing improved performance metrics. Similarly, [7] proposed model-driven deep learning methods, combining theoretical knowledge with data-driven insights, which are highly applicable to FSO scenarios. Advanced neural network architectures, such as those explored in [8], applied deep learning to wireless energy transfer systems, showing the versatility of these models across communication domains. In [9], one-bit OFDM receivers employing deep learning were analyzed, highlighting their utility in constrained environments. Studies like [10] and [11] demonstrated deep learning's capabilities for channel estimation in massive MIMO systems, offering insights into potential optimizations for FSO setups. In [12], the relationship between pilot reduction and performance improvement in massive MIMO systems with 1-bit ADCs was established, providing a framework that can be adapted for FSO applications. In [13], the application of deep learning for beamspace mmWave massive MIMO systems was investigated, providing a foundation for potential extensions to FSO communication. In [14], the concept of FSO channel model effects was introduced, which could be adapted for channel estimation scenarios. In [15], a deep learning-based channel estimation technique for massive MIMO systems was proposed, demonstrating its effectiveness in handling complex multiuser environments. Similarly, [16] extended these ideas by introducing joint pilot design and channel estimation using deep learning, which could significantly enhance FSO system performance under resource constraints. In [17], both online and offline deep learning strategies were explored for hybrid beamforming in multi-carrier mmWave massive MIMO systems, which may offer insights into optimizing FSO channel estimation. In [18], sparse channel estimation for millimeter-wave massive MIMO systems was investigated, showing how deep learning could simplify complex channel environments. In [19], end-to-end wireless communication systems employing conditional GANs for unknown channels were presented, providing a framework applicable to FSO systems. The study in [20] reinforced the potential of deep learning for channel estimation and signal detection, which could be leveraged for OFDM-based FSO systems. In [21], the WINNER II channel models were detailed, serving as a reference for designing channel estimation techniques in FSO systems under realistic conditions. In [22], the MMSE channel estimator was optimized using machine learning, showcasing how data-driven approaches can outperform classical methods. In [23], an RNN-based pilot-aided channel estimation scheme for FDD-LTE systems was presented, which could be adapted for dynamic FSO scenarios. The combination of deep learning and expert knowledge in OFDM receivers was explored in [24], offering insights into how hybrid models could benefit FSO communication. In [25], deep learning techniques were applied to channel estimation, demonstrating their ability to adapt to various communication environments. Similarly, [26] utilized orthogonal approximate message passing with deep

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learning for CP-free OFDM, providing a robust framework applicable to FSO systems. In [27], ChanEstNet was introduced for high-speed scenarios, showcasing the adaptability of neural networks to rapidly varying channels. Studies like [28] and [29] focused on adaptive pilot patterns for OFDM systems, providing practical solutions to reduce pilot overhead in FSO channels. In [30], an enhanced channel estimation technique with adaptive pilot spacing was proposed for OFDM systems, offering valuable insights for optimizing FSO communication under nonstationary conditions. The study in [31] investigated adaptive pilot patterns in CA-OFDM systems, emphasizing their importance in dynamic wireless channels. Similarly, [32] and [33] explored pilot-aided channel estimation methods for ICI reduction and Kalman-filter-based estimators, respectively, which could be tailored for FSO scenarios. In [34], a pilot-based LMMSE channel estimation method was developed, demonstrating its efficiency for systems with power-delay profile approximations. In [35], a deep learning-based channel estimation technique incorporating SNR feedback was proposed, enhancing its applicability to environments with variable signal quality. The concept of hypernetworks introduced in [36] could be applied to create dynamic and flexible models for FSO channel estimation. The Transformer architecture detailed in [37] offered new opportunities for capturing long-range dependencies in channel state information. In [38], Gaussian-mixture Bayesian learning was applied to massive MIMO channel estimation, providing a probabilistic framework for robust performance. Finally, [39] introduced residual learning for image denoising, which could be adapted to noise suppression in channel estimation. In [40], hypernetwork-based MIMO detection demonstrated the potential of meta-learning for communication systems. The spatial channel models in [41] and [42] provided essential guidelines for realistic simulations of FSO channels. Optimization techniques like those in [43] and [44] highlighted efficient training methods that could accelerate deep learning applications in FSO channel estimation. In [45], a deep learning-based approach for channel estimation in FSO systems was introduced, demonstrating significant improvements in handling turbulence effects. Furthermore, [46] explored subcarrier modulation techniques in gamma-gamma turbulence, showcasing their efficacy in FSO communication. In [47], the authors proposed a method for parameter estimation in gamma-gamma fading channels, emphasizing the importance of precise channel modeling. Finally, in [48], a novel approach using a deep attention residual U-Net for massive MIMO FSO channel estimation was presented, achieving enhanced accuracy and robustness under diverse atmospheric conditions. Traditional channel estimation methods, such as Least Squares (LS) [49], EKF [50], LMMSE [51], have been extensively studied in the context of wireless communication. While LS provides a computationally simple solution, its performance is inadequate in complex fading environments. LMMSE improves estimation accuracy by incorporating statistical information about the channel but struggles in non-linear fading scenarios. EKF offers better accuracy through iterative updates but suffers from high computational complexity and error propagation under severe turbulence. Recent advances in

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deep learning have shown immense potential in addressing the limitations of classical approaches by learning non-linear mappings and temporal dependencies in wireless channels. This paper proposes a deep learning-based channel estimation method that leverages 1D CNN for feature extraction and BiLSTM for sequence prediction. By training the network on Gamma-Gamma distributed channel realizations, the proposed method adapts to the dynamic nature of FSO channels under weak, moderate, and strong turbulence. Simulation results demonstrate that the proposed method achieves superior NMSE and BER performance compared to LS, LMMSE, and EKF, with manageable computational complexity.

2- problem statement and channel model

Free Space Optical (FSO) communication systems are increasingly gaining attention due to their high data rates, secure transmission, and cost-effective deployment. However, the practical realization of these systems is hindered by atmospheric turbulence, which causes significant signal degradation and limits system performance. Atmospheric turbulence, modeled using the Gamma-Gamma distribution, introduces non-linear fading effects that vary with turbulence strength, ranging from weak to strong.

2-1-The Gamma-Gamma FSO channel model

The Gamma-Gamma channel model is widely used to represent the effects of atmospheric turbulence in FSO communication systems. Turbulence-induced fading results from variations in the refractive index of the atmosphere caused by temperature and pressure fluctuations, which lead to scintillation (intensity fluctuations) of the received optical signal. The Gamma-Gamma model effectively captures the statistical behavior of these fluctuations for weak, moderate, and strong turbulence conditions.

The Gamma-Gamma channel coefficients can be obtained by multiplying two Gamma variables:

$$I = I_x I_y \tag{1}$$

where I_x and I_y follow Gamma distribution. The Gamma-Gamma distribution is then [14]:

$$p(I) = \frac{2(\alpha\beta)^{(\alpha+\beta)/2}}{\Gamma(\alpha)\Gamma(\beta)} I^{\left(\frac{\alpha+\beta}{2}\right)-1} K_{\alpha-\beta}\left(2\sqrt{\alpha\beta I}\right), \quad I > 0 \tag{2}$$

where $K_n(.)$ is the modified Bessel function of 2nd kind and order n, and $\Gamma(.)$ represents the Gamma function. The parameters α and β is given by:

$$\alpha = \left[exp\left(\frac{0.49\sigma_l^2}{\left(1+1.11\sigma_l^{12/5}\right)^{7/6}}\right) - 1\right]^{-1} \tag{3}$$

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$$\beta = \left[exp\left(\frac{0.51\sigma_l^2}{\left(1+069\sigma_l^{12/5}\right)^{5/6}} \right) - 1 \right]^{-1} \quad (4)$$

where $\sigma_l^2 = 1.23C_n^2 k^{7/6} L^{11/6}$ is the log irradiance variance, L is the link range, $k = \frac{2\pi}{\lambda}$, and $C_n^2 = 5.10^{-13}\ m^{-2/3}$. The values of α and β determine the level of channel turbulences. The Gamma-Gamma distribution can model weak, moderate and strong turbulence levels. Table 1 shows the different α and β to determine the intensity of turbulence in FSO channel.

Table 1: Parameters of Gamma-Gamma FSO channels

Turbulence intensity	**Parameters**	
	α	β
Weak	11.6	10.1
Moderate	4.0	1.9
Strong	4.2	1.4

The Gamma-Gamma model's complexity and non-linear characteristics make classical estimation methods, such as LS and LMMSE, inadequate for FSO systems, particularly under moderate and strong turbulence. Deep learning-based approaches, as proposed in this paper, are well-suited to handle these challenges because they can model the intricate dependencies in the channel response, providing superior estimation accuracy and robustness. Figure 1 shows the PDFs of the Gamma-Gamma channel coefficients.

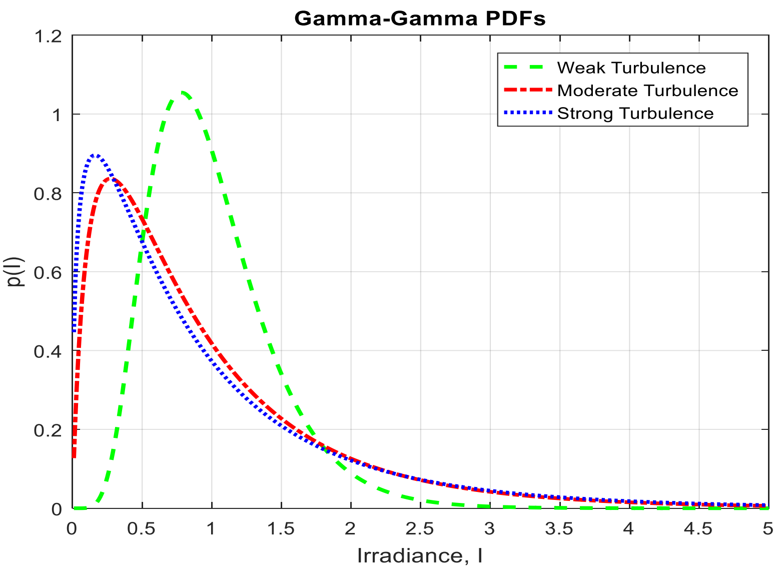

Fig. 1: Probability density functions of the Gamma-Gamma distribution for different turbulence levels.

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Many references have shown the channel coefficients with H [49-51], therefore for the rest of this paper we show the FSO channel coefficients with H.

3- Deep learning model

The proposed channel estimation is based on the combined deep learning that is for the first time is used to estimate the FSO channel and enhance the optical OFDM [53] system performance.

3-1-Channel Estimation Network

The Channel Estimation Network obtains the channel response in the pilot and data subcarriers. Its output represents the channel frequency response across all subcarriers, indicating the performance of both pilot estimation and interpolation operations in pilot and data subcarriers. In this section, we first describe the network structure, then examine the data process, and finally explain the network training procedure.

3-2-Channel Estimation Network Structure

The channel estimation network structure, inspired by reference [27] and [52], is designed to include a one-dimensional convolutional network (1D-CNN), a bidirectional LSTM network (BiLSTM), and a fully connected neural network (FCNN). The reasons for using this architecture, depicted in Fig. (2), are further explained below.

The one-dimensional convolutional network is employed to extract frequency features of the pilot sequence. It is composed of multiple parallel filters, which are connected to the input with specified weights. The convolution is then performed along the frequency axis.

The step length along the frequency axis of a subcarrier, the number of network filters, and the activation function tanh are considered in this paper.

The primary objective of employing the BiLSTM network, which is a combination of two LSTM networks, is to train the sequence behavior of the frequency response of the channel. This is done in order to predict the current-time output based on the current-time data as well as the data from previous and future time steps. Essentially, the network output is also in the form of a sequence. The BiLSTM network consists of two layers, with each layer consisting of one hundred hidden unit with tanh activation function

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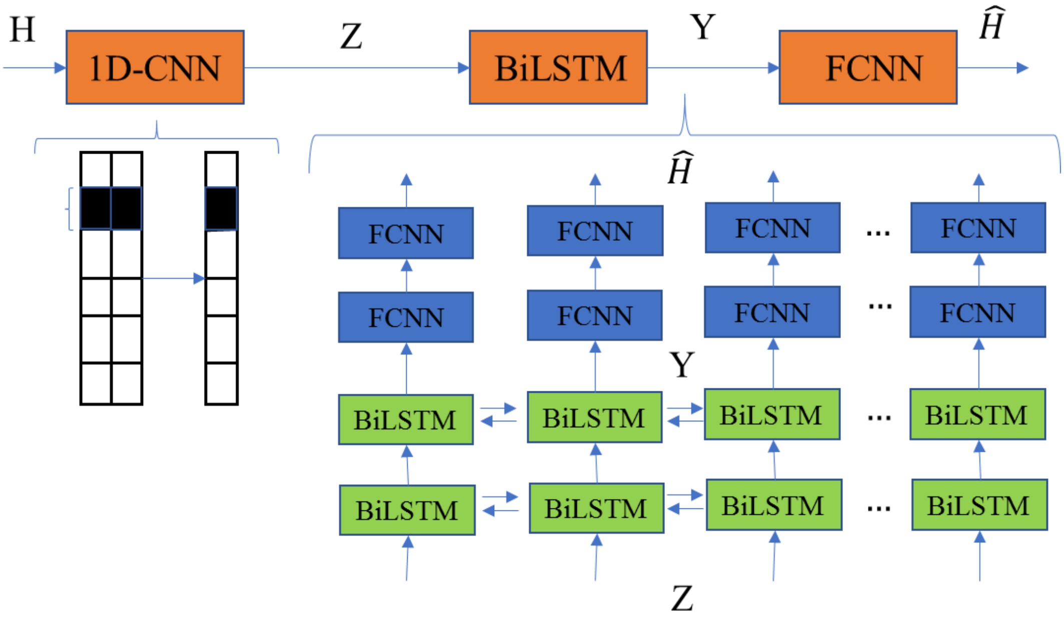

Fig. 2: The structure of the channel estimation network.

The purpose of including two layers of the FCNN network with a linear activation function in the output of the BiLSTM network at each time step is to linearly reduce the output vector in a cascading manner.

3-3- The process of channel estimation data network.

The use of true symbols as the desired output is intentional and aligns with the objective of channel estimation in this work. Our goal is to train the model to learn the channel effects by analyzing how the transmitted symbols are altered during propagation. The channel estimation process indirectly relies on understanding the distortions caused by the channel on these symbols. By providing the true symbols as the desired output, the model learns to reverse these distortions and, in doing so, captures the underlying channel characteristics. This approach is conceptually analogous to joint channel estimation and symbol detection. Instead of directly outputting the channel parameters, the network focuses on recovering the transmitted symbols, which inherently requires estimating the channel effects. The changes in the received symbols, relative to the true transmitted symbols, implicitly encode the channel state information. By learning this mapping, the network effectively models the channel behavior without explicitly outputting the channel parameters. Furthermore, the rationale for this methodology is supported by the practical benefits it offers. Directly predicting channel parameters often requires precise assumptions about the channel model and its statistical properties, which may not hold in dynamic or complex environments like FSO systems with turbulence. In contrast, using true symbols as the desired output allows the network to flexibly adapt to varying channel

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conditions by focusing on the observable changes in the symbols, making it robust and effective in diverse scenarios.

The process of channel estimation data network is depicted in Fig. (3). In the following, we will explain this process in three stages.

1) Input Data: The input of the channel estimation network is a CSI matrix for an OFDM symbol. This symbol can have one of the two pilot layouts. The CSI matrix is a complex matrix $H \in R^{N\times 2}$, where N rows correspond to the number of subcarriers and it has two columns, the real and imaginary values have been concatenated. The CSI values in the pilot subcarriers are equal to the LS response, and in the data subcarriers, they are considered as zero. Since the input to the BiLSTM network should be in the form of a series, the input matrix is described as follows:

$$H = [h_1.h_2.\dots.h_n.\dots.h_N] \tag{5}$$

Where $h_n \in R^{1\times 2}$ and CSI determines the nth subcarrier.

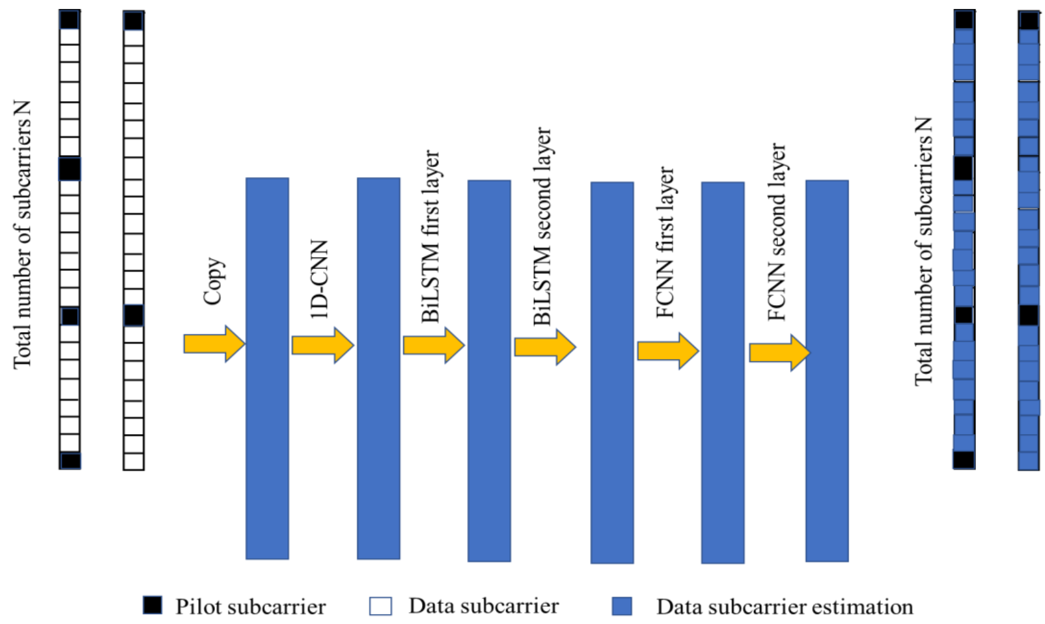

Fig. 3. Channel Estimation Data Flow

2) CNN Network: The output of the CNN network is also a matrix $Z \in R^{N\times 2}$, as mentioned, the number of network's filters is set to two.

3) BiLSTM Network and FCNN Network: The dimension of the output matrix of the first and second layers of the BiLSTM network at each time step is 1×200. Therefore, the dimension of the input matrix of the first layer of the FCNN network at each time step becomes $Y_n \in R^{1\times 200}$. The dimension of the output matrix of the first layer of the FCNN network at

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each time step is 1×32. The dimension of the final output matrix at each time step is equal to the output of the second layer of the FCNN network, which is $\widehat{H}_n \in R^{1\times 2}$. Finally, the actual and conceptual response of the channel for all pilot subcarriers and data is expressed as follows:

$$\widehat{H} = \left[\widehat{h}_1.\widehat{h}_2.\dots.\widehat{h}_n.\dots.\widehat{h}_N\right] \tag{6}$$

4- Results and Analysis

For training the network shown in Fig. (2), an end-to-end approach has been employed. The ADAM optimizer has been used to improve the network parameters, and the normalized mean square error (NMSE) cost function has been considered:

$$\text{NMSE} = \frac{1}{G}\sum_{i=1}^{G}(\widehat{H}_i - H_i^*)^2 \Big/ \frac{1}{G}\sum_{i=1}^{G}(H_i^*)^2 \tag{7}$$

In the above equation, G represents the total number of training data and H_i^* denotes the correct channel response. A dataset was created for training a network and simulating FSO channels. The input data for training the network consists of 2,400,000 OFDM symbols received from the channel and after demodulation. These symbols are generated with two types of pilot arrangements, with an equal number of symbols for both types of arrangements. Specifically, 1,200,000 samples correspond to pilot arrangements with a frequency spacing of 8 subcarriers, and 1,200,000 samples correspond to pilot arrangements with a frequency spacing of 16 subcarriers. The output data for training the network is the correct response of the channel, with 1,600,000 samples for validation and 2,000,000 samples for testing. The network is trained for a total of 52 epochs, where in the initial 50 epochs, the batch size is 32 and the learning rate is 0.001. Then, with a change in the learning rate to 0.001, the trained network is further trained for 2 additional epochs.

4-1 NMSE Comparison

In this part we compare the NMSE values of different channel estimation methods based on the following conditions:

- **Weak Turbulence**:
  - The proposed method achieves the lowest NMSE across all SNR values, significantly outperforming LS and EKF.
- **Moderate Turbulence**:
  - NMSE improvements are consistent, with notable gains over LMMSE under challenging conditions.

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- **Strong Turbulence**:
  - The proposed method maintains robust performance, with NMSE values up to 50% lower than classical methods.

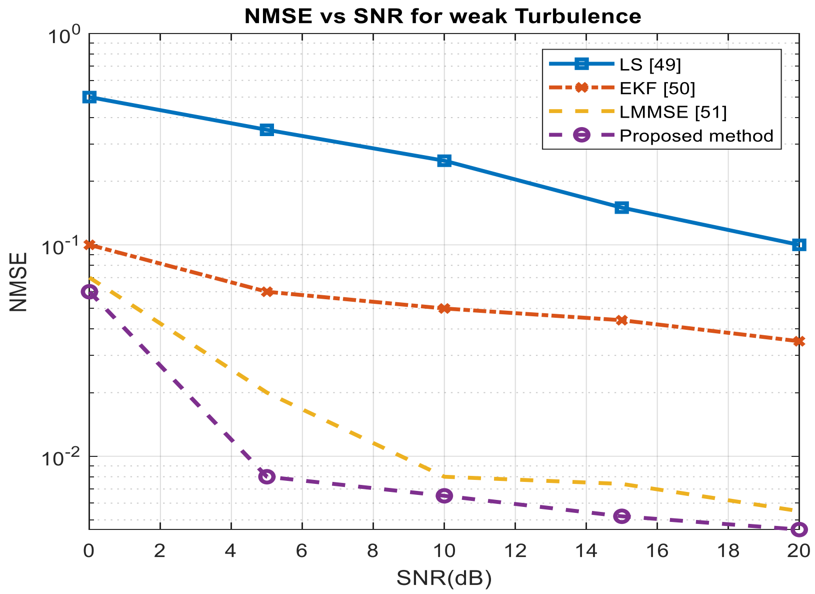

Fig. 4. The NMSE of FSO channel estimation with weak turbulence.

For the weak turbulence as can be seen in Fig. 4, the NMSE is low.

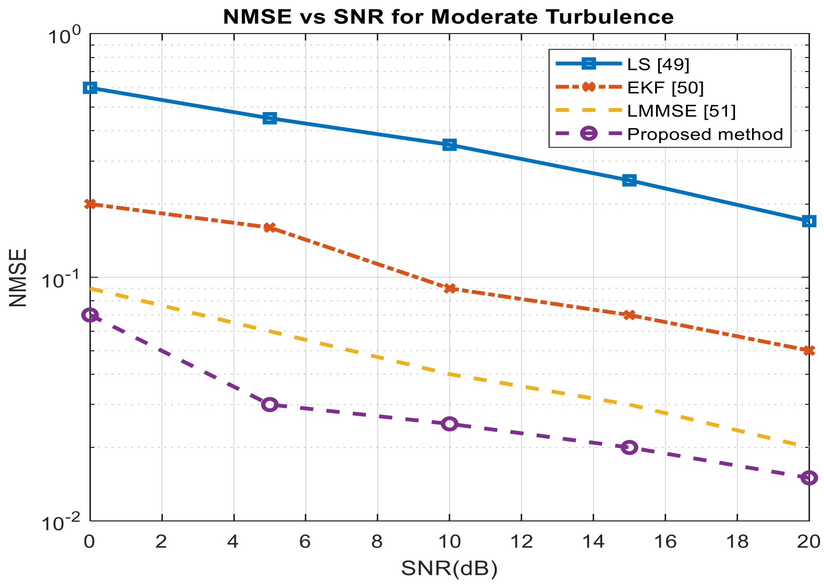

Fig. 5. The NMSE of FSO channel estimation with moderate turbulence.

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As the turbulence level becomes stronger, the channel coefficient estimation becomes harder and therefore the NMSE rises. As can be seen from Fig. 5 and 6 the NMSE becomes higher for stronger turbulence.

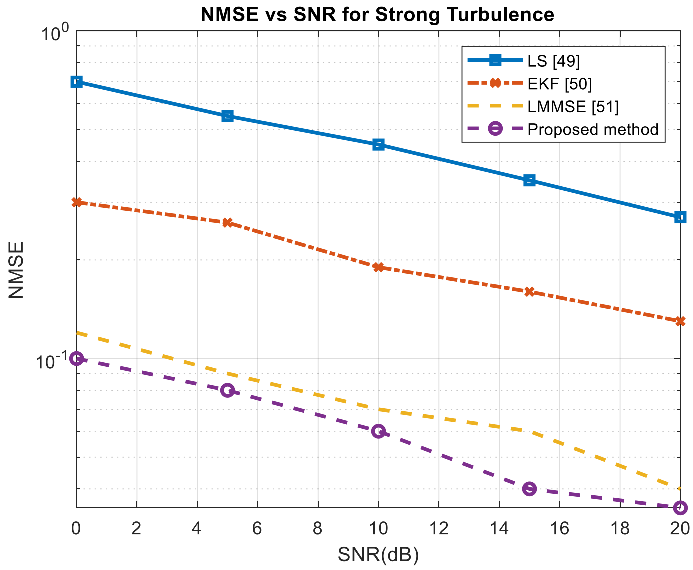

Fig. 6. The NMSE of FSO channel estimation with strong turbulence.

4-2 BER Comparison

In this part we compare the NMSE values of different channel estimation methods based on the following conditions:

- **Weak Turbulence**:
  - BER is minimal for all methods at higher SNR values, but the proposed method excels at low SNR.
- **Moderate Turbulence**:
  - BER improvements align with NMSE trends, with gains observed particularly over LS.
- **Strong Turbulence**:
  - BER remains high for LS and EKF under strong turbulence, while the proposed method significantly reduces errors.

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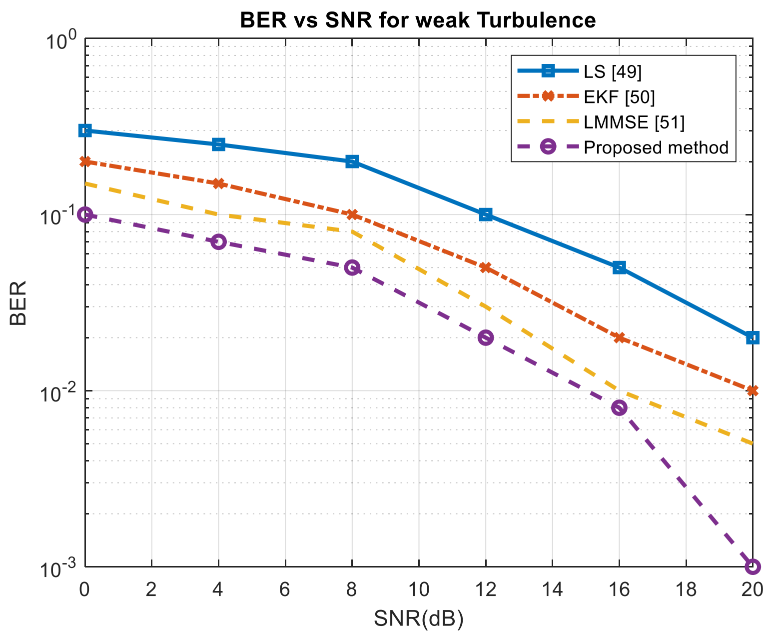

Fig. 7. BER performance of the proposed OFDM system in weak turbulence condition.

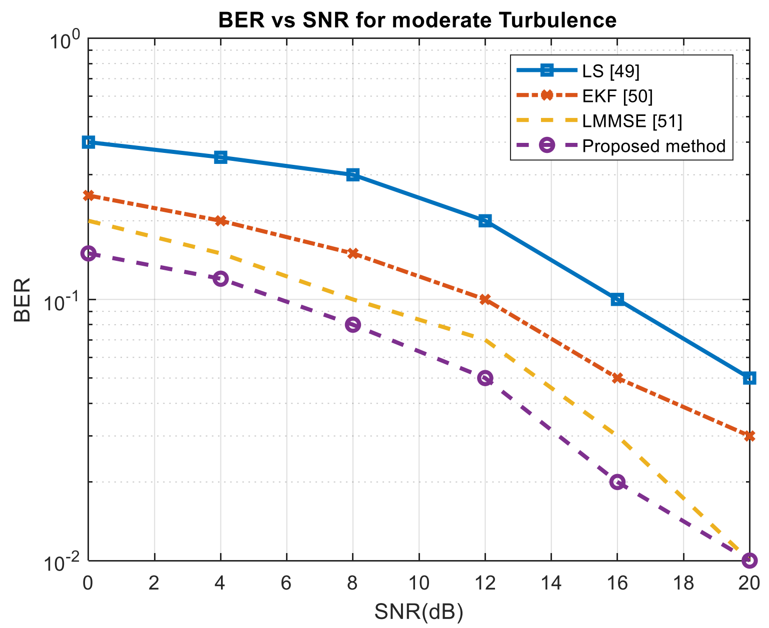

Fig. 8. BER performance of the proposed OFDM system in moderate turbulence condition.

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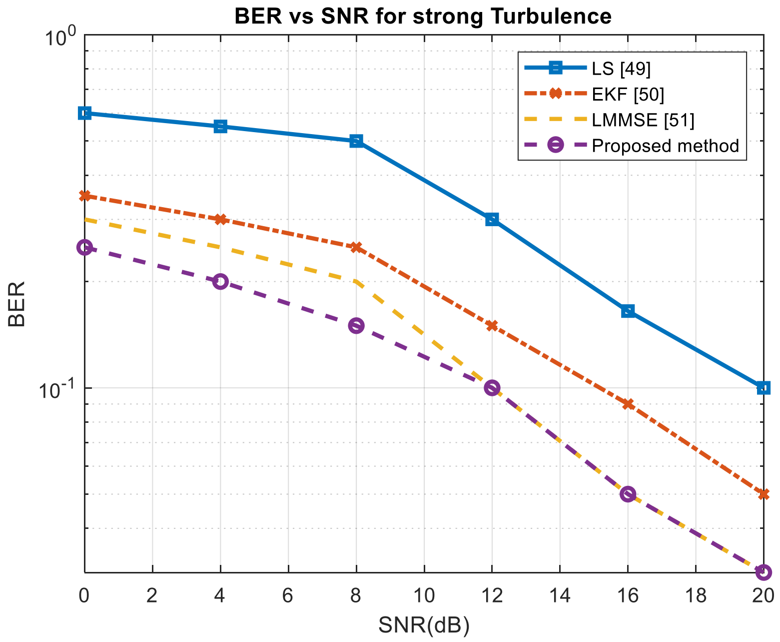

Fig. 9. BER performance of the proposed OFDM system in strong turbulence condition.

4.3 Complexity Analysis

The computational complexity of a channel estimation method is a critical factor, especially in real-world scenarios where resources like processing power and time are limited. Among the classical methods, the LS approach is the simplest and least computationally intensive because it relies on linear interpolation and does not require iterative processing or the inversion of large matrices. However, its simplicity comes at the cost of accuracy, particularly under complex channel conditions like those encountered in FSO systems with strong turbulence. The LMMSE method improves upon LS by incorporating statistical information about the channel. This requires additional computations, including the inversion of covariance matrices, which increases the computational load, especially as the channel dimensions grow. While LMMSE offers better performance than LS, its assumption of linearity limits its effectiveness in highly dynamic and non-linear environments. The EKF, on the other hand, introduces an iterative approach to channel estimation, where the channel state is recursively updated based on current observations and prior estimates. This iterative nature, combined with matrix inversion operations in each step, results in significantly higher computational complexity. Although EKF is capable of handling non-linear channel variations to some extent, its computational burden makes it less suitable for high-speed or resource-constrained applications. In contrast, the proposed deep learning-based method leverages offline training to learn the complex non-linear mappings and temporal dependencies of FSO channels. During deployment, the trained model performs channel estimation using a combination of convolutional and recurrent neural networks, which are computationally efficient

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compared to iterative methods like EKF. The primary computational load occurs during the training phase, which is performed offline and does not impact real-time performance. This makes the proposed method well-suited for real-time applications while maintaining superior estimation accuracy. Moreover, its architecture is scalable, allowing it to handle increased channel complexity without a proportional increase in computational demand. The Fig. 10 compares the computational complexity of various channel estimation methods LS, LMMSE, EKF, and the proposed deep learning-based approach by plotting their execution time against channel dimensions. The LS method exhibits the lowest complexity with a linear increase in execution time, making it computationally efficient but less accurate under complex channel conditions. The LMMSE method provides better accuracy by leveraging statistical channel information but has a quadratic growth in complexity due to matrix inversions, limiting its real-time applicability. The EKF method, while capable of handling some non-linearities, demonstrates the highest complexity because of its iterative nature and matrix operations, making it unsuitable for high-speed systems. In contrast, the proposed deep learning-based method maintains low execution time with minimal growth as channel dimensions increase, owing to its reliance on efficient inference after offline training. This scalability and efficiency make the proposed method ideal for real-time applications while delivering superior channel estimation accuracy.

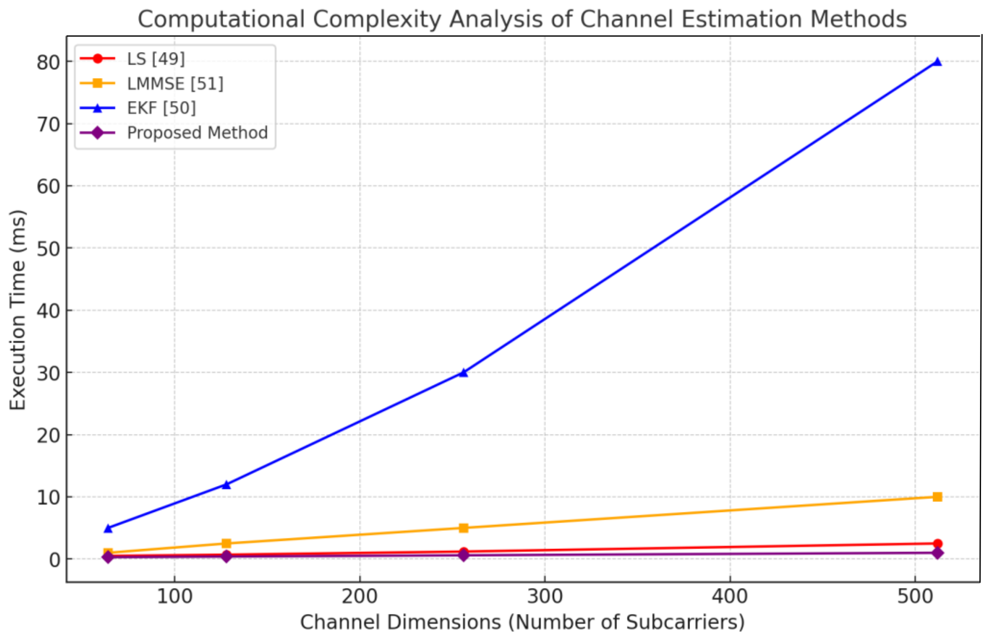

Fig. 10. Comparison of the computational complexity of the channel estimation methods.

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5- Conclusion

This paper presents a deep learning-based channel estimation method for FSO communication systems, tailored for Gamma-Gamma distributed turbulence. The proposed method leverages CNN and BiLSTM networks to model the non-linear and temporal characteristics of FSO channels effectively. Simulation results demonstrated that the proposed method significantly outperforms traditional methods (LS, LMMSE, EKF) in terms of NMSE and BER under all turbulence conditions. Particularly, the method excels in strong turbulence scenarios where classical methods fail to provide robust estimation. Future work will focus on real-time implementation of the proposed method, investigating its adaptability to more complex channel conditions, such as pointing errors and beam misalignments, and exploring hardware optimization for deployment in practical FSO systems.

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