Machine Learning-Based Enhancement of Free-Space Optical Communications Against Atmospheric Turbulence

B.Sc. Abidur Rahman
Chair of Information and Coding Theory
Christian-Albrechts-Universität zu Kiel
Kiel, Germany
stu232556@mail.uni-kiel.de

***Abstract*—Free-space optical (FSO) communication is a wireless communication technology that operates in the range between near visible and infrared light spectrum. The use of laser or light emitting diodes for data transmission in FSO communication is similar to that of optical communication through optical fiber, but it operates in unguided wireless medium like radio communication (RC). Although FSO could be considered as an advantageous alternative of RC in terms of higher data rate, unlicensed operation and low latency etc., it suffers from several factors such as pointing error loss, atmospheric turbulence (AT), absorption loss, scattering loss and so on. Among them, AT is mainly responsible for the performance degradation of FSO systems. Several approaches are available to mitigate AT for system optimization, such as adaptive modulation techniques and machine learning (ML). In this paper, we first analyze the different AT models including their impact on data transmission, followed by the results of implementing ML to combat this problem.**

***Index Terms*—Free-space optical communication, atmospheric turbulence, machine learning/deep learning, orbital angular momentum, scintillation effect.**

I. Introduction

In the last few decades, *radio frequency* (RF) technology has become synonymous with wireless communications for its large-scale development and deployment [14]. Due to the exponential increase in the number of users, RF technology has been evolved decade by decade and different access schemes have been proposed such as *time division multiple access* (TDMA), *frequency division multiple access* (FDMA), *code division multiple access* (CDMA), *orthogonal frequency division multiple access* (OFDMA) and so on [15]. However, RF technology suffers from spectrum scarcity, i.e. the available spectrum is almost entirely used up and there is very little room left to increase the bandwidth. In addition, it requires FCC license and efficient management from the operator side for deployment and profit margin respectively [16], [3].

Free-space optical (FSO) communication is a viable alternative to RF in the wireless medium with the optical base for broadband communications. In FSO, the optical carrier is modulated according to the data symbol and transmitted through the atmosphere using a transceiver. This is a point-to-point communication technology, so line of sight (LOS) is a mandatory requirement for its operation. Although it is confusing whether FSO belongs to the wireless or optical group based on its dual nature, but the authors in [3] confirmed that it is mainly an optical technology. FSO can be divided into two broad branches, namely indoor and outdoor system, where generally light emitting diodes (LEDs) for visible light spectrum and laser beams for infrared spectrum are used respectively [9], [14]. The field of application of FSO ranges from satellite-to-satellite crosslinks, satellite-to-ground optical links, aircraft, ships, unmanned aerial vehicles (UAVs) and much more [9], [2], [7]. FSO has advantages over both RF and fiber optic (guided laser beam communication) technology in terms of cost efficiency, last mile coverage, chip-to-chip/board-to-board communication, security, etc. [3], [14].

Considered as the next frontier for network-centric connectivity, FSO largely suffers from the intermediate medium (atmosphere) between the transmitter and the receiver along with other impairments such as ambient noise, thermal noise, dark current, shot noise etc. at the receiver side [9]. In this paper our main concern is to address the impairments caused by the atmosphere on the received signal and explain some *machine learning* (ML)/*deep learning* (DL)-based approaches to replace the conventional way to overcome these issues while maintaining the *quality of service* (QoS) of the system.

The rest of this paper is organized as follows.

- Section II provides an overview of atmospheric impairments (e.g., atmospheric loss and atmospheric turbulence) along with some empirical models for atmospheric description.
- In Section III, we mention some papers that have focused on improving the performance of the FSO system using ML/DL and provide a brief comparison between them.
- The conclusion of this paper is drawn in Section IV.

II. Atmospheric Interference and Models

During the propagation of the optical wave in the wireless medium, two factors significantly affect the light wave, i.e. extinction and refractive index turbulence, which are associated with the attenuation of the optical intensity and the fluctuation of the received optical signal, respectively [2]. Both effects are briefly described in the first part of this section, while the theories used to model atmospheric turbulence are explained in the second part.

A. Atmospheric Impairments

1) Absorption and Scattering Loss: Absorption loss refers to the attenuation of signal strength as it propagates through the air. The major contributors to strong attenuation are haze, fog, dust, and rain, although attenuation also occurs in clear weather due to air molecules [16]. According to [2] and [5], the path loss/attenuation is given by the Beer-Lambert law as

$$P_r = P_t \cdot e^{\alpha_e(\lambda).L}. \tag{1}$$

Where P_r and P_t are the received and transmitted optical powers, respectively, $\alpha_e(\lambda)$ is the attenuation coefficient in $\mathrm{dB/km}$, and L is the link propagation distance. The visibility of the link, V, is an important parameter to determine the value of $\alpha_e(\lambda)$, defined as the visual range of the wavelength at $532\mathrm{nm}$ [6] where the transmitted light intensity decreases by 2% [2], [5]. The authors mention in [2] that attenuation is wavelength dependent, but [16] revises this assertion to say that wavelength dependence occurs only in haze, whereas in fog, attenuation is wavelength independent. For FSO optimization, efficient optical windows should be considered where attenuation is less pronounced [2].

Scattering refers to the redistribution of optical energy in different directions and is a wavelength and altitude dependent phenomenon that causes spatial, angular and temporal scattering and thus reduction of light intensity [16], [14]. This effect occurs due to the presence of air molecules and aerosols (solid and liquid particles suspended in the air) that collide with the optical beam. Scattering becomes detrimental if the size of the particles is on the same order that of the wavelength of light [14], [9]. For particles (e.g. gas molecules) smaller than the wavelength, Rayleigh scattering is dominant and wavelength dependent, i.e. smaller wavelengths scatter more [9]. [4]. Mie scattering is another type of scattering that occurs when the particle size is comparable to the wavelength of light [16], [9]. If the gas molecules are much larger than the wavelength of the light beam, then geometrical-optical models are used to describe the scattering effects [9], [16]. It is experimentally proven that fog is the most extreme case that can occur during FSO communication [14].

2) Atmospheric Turbulence: This phenomenon, called *atmospheric turbulence* (AT), is caused by thermal heating from sunlight and wind. This creates temperature and pressure gradients in the atmosphere. These gradients lead to the formation of inhomogeneous air cells with varying *refractive indices* (RI). These variations cause fluctuations in the phase of the propagating optical waves, resulting in image dancing in the receiver aperture in both spatial and temporal form. This fluctuating effect is called the *scintillation effect* [7], [3] and is measured by *scintillation index* (SI) [2].

AT is mainly divided into three branches, i.e. weak (SI < 1), moderate (SI $= 1$) and strong (SI > 1) AT [10]. C_n^2, also known as the refractive index parameter, is used to describe the strength of AT, given by [6]

$$C_n^2 = \left(79 \times 10^{-6} \frac{P}{T^2}\right) C_T^2, \quad (m^{-2/3}). \tag{2}$$

where, $P\,(\text{constant pressure}) = 970\,\mathrm{mbar}$, T is the temperature in Kelvin scale, and $C_T^2 = \sqrt{\langle \partial T^2 \rangle} r^{-1/3}$ is the temperature structure parameter.

B. Atmospheric Turbulence Models

In RF communications, various distribution models (e.g., Rayleigh, Rician, Weibull) are used to describe the channel's multipath fading behavior, where the envelope of the signal, $a(t)$, is considered, whereas in FSO, the interest is in the intensity fluctuation of the received signal, given by $I(t) \propto a^2(t)$ due to AT [12]. Based on the AT profile, several empirical models have been proposed. For example, the log-normal distribution is used only for weak AT [12]. The probability density function of the received optical signal is given by [10]

$$f_I(I) = \frac{1}{2I\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(\ln I - \mu)^2}{2\sigma^2}\right), \quad I > 0. \tag{3}$$

Where, $I =$ signal intensity, μ and σ are the log-mean and log-irradiance variance of the distribution respectively. Rytov variance, σ_r is used to define the scintillation effect, given by [10]

$$\sigma_r^2 = \sigma^2 = 1.23\, C_n^2\, k^{7/6}\, L^{11/6}. \tag{4}$$

Here, K and L denote the optical wave number and the propagation path, respectively.

The most widely used channel model is the gamma-gamma distribution, which provides a joint distribution for weak and strong turbulence effects and is described as [10]

$$f(I) = \frac{2(\alpha\beta)^{(\frac{\alpha+\beta}{2})}}{\Gamma(\alpha)\Gamma(\beta)} \cdot I^{\frac{(\alpha-\beta)-2}{2}} \cdot K_{\alpha-\beta}(2\sqrt{\alpha\beta I}). \tag{5}$$

Here, K denotes the second-order Basel function, Γ is the gamma function, and α and β represent small-scale and large-scale turbulence effects, respectively. More of these gamma-gamma and other atmospheric distributions are described in [10].

Various schemes have been proposed to tackle the effect of AT on the transmitted signal to achieve a reliable link between the transceivers in terms of bit error rate (BER). In [12], the authors proposed a hybrid 5G RF/FSO transmission system assuming Malaga-$\mathcal{M}$ channel. In [4], a multi-beam WDM-FSO system has been proposed for haze conditions. The performance of a number of array receivers is experimented in [5]. A measurement of the switching system between spatial diversity and spatial multiplexing has been made in [13]. In the next section we will elaborate some methods to mitigate the effect of AT for specific condition based on ML/DL.

III. ML-based Approaches

Lionis et al. in [17] focus on predicting the performance of an FSO link based on seven macroscopic meteorological features, i.e., wind speed, ambient temperature, relative humidity, air-sea temperature difference, dew point, solar flux, and marine relative pressure. In this work, only supervised learning methods for regression models are considered where the received signal strength (RSSI) is the output of the regression models. Five different models i.e., KNN, decision trees (DT), gradient boosting regression (GBR), random forest (RF) and artificial neural network (ANN) have been considered for the prediction task to get a better comparison between their results.

The FSO system consists of a path length of $2958\mathrm{m}$ at a wavelength of $850\mathrm{nm}$. The horizontal path was about $35\mathrm{m}$ above the sea surface, and more than 95% of it was over the water [17]. To measure the air-sea temperature difference, an online weather statistics database is also used. The weather parameters are measured every minute, twenty-four hours a day. The dataset has been divided into 80% and 20% for training and testing the models respectively, but for ANN only it is $70\%/15\%/15\%$ for training, validation and testing respectively. The relative importance of each weather feature on RSSI is also plotted in this paper. RMSE and R^2 scores are considered for the analysis of the model performance.

Tab. I illustrates the full performance comparison spectrum of the regression models.

TABLE I: Performance comparison of RSSI prediction models [Source: [17]].

Approach	R^2			RMSE		
	Training	Validation	Test	Training	Validation	Test
KNN	0.93	-	0.85	8.29	-	12.48
DT	0.9764	-	0.91	4.9	-	9.71
RF	0.994	-	0.947	2.7	-	7.37
GBR	-	-	0.9417	-	-	7.71
ANN	0.9496	0.9468	0.94867	10.06	10.19	10.17

It is clearly seen that the ANN model provides the best accuracy with a R^2 value of 0.94867 at the cost of higher computational cost, while the KNN shows the worst performance among all the models. Additionally, it has been drawn that the ambient temperature has the highest parametric importance on the RSSI value.

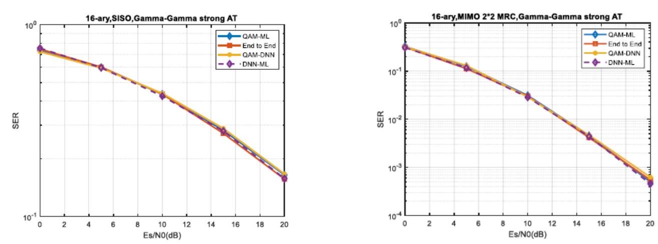
In [1], the authors demonstrate three *deep neural network* (DNN)-based system architectures for both SISO (single input single output) and MIMO (multiple input multiple output) schemes to combat the AT effects on the transmitted signal. Different turbulence levels (strong, moderate and weak). modulation orders and combining schemes (maximum ratio, equal gain, and selection combining) are also considered for each case.

In the first architecture, the QAM constellation DNN-based detection is considered, where the symbol detection is performed by the DNN. In the second case, a DNN-based constellation shaper ML detection scheme is used to map the transmitted symbols onto the constellation diagram using DNN. In the third case and end-to-end DNN based model is experimented where DNN is used for both mapping the symbols and detecting [1]. The hyperparameters of the DNN architecture are given in Tab. II. In each architecture, a gamma-gamma AT model is considered with different strengths (see Sec. II-B).

TABLE II: Tuned Hyperparameters in the DNN architecture [Source: [1]].

Hyperparameter	Value
Modulation Order	16/4
Number of Layers	4
Number of Hidden Neurons	40
Batch Size	$16 \times 256 \times 16$
Sample Size / Batch Size	4
Number of Iterations	1000
Activation Function	Relu/Crelu
Loss Function	Softmax Cross Entropy with logits_v2
Optimizer	Adam
Learning Rate	0.005
Gamma-Gamma Atmospheric Turbulence Intensity	Strong ($\alpha = 4.2, \beta = 1.4$) Moderate ($\alpha = 4, \beta = 1.9$) Weak ($\alpha = 11.6, \beta = 10.1$)

Fig. 1a illustrates the performance of four different architectures for 16-ary, SISO, Gamma-Gamma strong AT. end-to-end DNN performs the same as DNN-ML while QAM-DNN's graph fits with QAM-ML. It is clearly observed that DNN-ML outperforms QAM-ML in terms of *symbol error rate* (SER), thus demonstrating the efficiency of DNN. In Fig. 1b, the performance metrics are considered for 2×2 MIMO-MRC scheme. The only difference can be seen that the performance margin between DNN-ML and QAM-ML is lower compared to the previous one. The advantage of implementing DNN lies in the lower system complexity, although to achieve the state-of-the-art performance, the hyperparameter tuning process should be given more concentration.



(a) Performance of different architectures based on SER of SISO-FSO structure.

(b) Performance of different architectures based on SER of 2×2 MIMO-FSO structure.

Fig. 1: SER vs. E_s/N_0 for QAM-ML, DNN-ML, QAM-DNN, and end-to-end DNN in SISO and MIMO [Source: [1]].

A joint AT-type detection and adaptive demodulation scheme has been proposed in [8] using *convolutional neural network* (CNN). In this paper, a fundamental property of the *Laguerre-Gaussian* (LG) beam called *orbital angular momentum* (OAM) has been exploited to modulate the information bits [11]. Theoretically, there are an infinite number of OAM states that represent different data symbols on the constellation diagram. By looking at the optical vortices (OV) of the received signal, it is possible to demodulate the symbol as well as the AT information [8].

In this proposed structure, a path length of $1000\mathrm{m}$, light wavelength of $1550\mathrm{nm}$, the Hill-Andrews AT model is considered. For faster processing, the received image is resized to 96×96 in resolution. 6 types of AT classes and 16 different OAM modes are considered. For each AT and OAM mode, 1200 images are collected and $2/3$rd of the images are used for training the CNN. Fig. 2 shows the performance of the CNN for detecting different classes of AT.

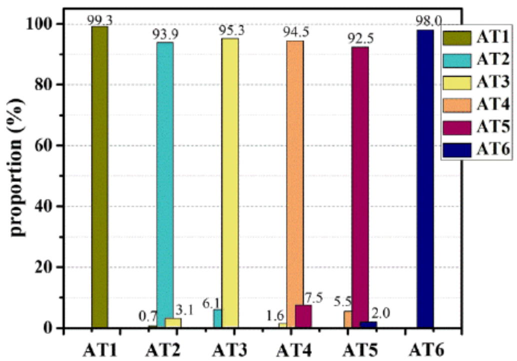


Fig. 2: Classification proportion of different AT by the CNN [Source: [8]].

The CNN performs well for the weakest and strongest AT with a detection accuracy of 99.3% and 98% respectively. When the CNN is trained to detect 4 types and AT, its performance is greatly increased but significantly lost when it is trained for 10 ATs. For demodulation, three OAM modes (4-OAM, 8-OAM, and 16-OAM) in four different AT regimes were experimented. It can be seen that the CNN gives the best accuracy for 8-OAM in the strongest AT case. Fig. 3 clearly shows the accuracy result.

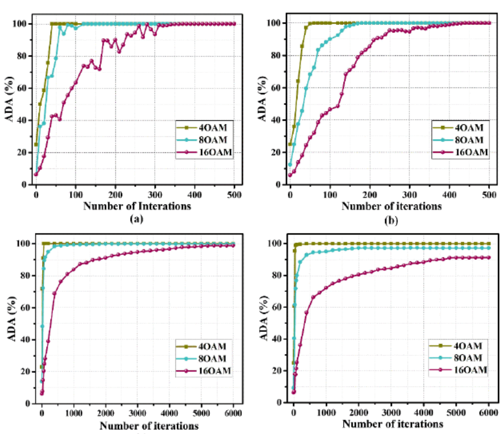


Fig. 3: Demodulation accuracy curve of the CNN for various OAM modes [Source: [8]].

IV. Conclusion

In this review paper, we provide an overview of some of the possibilities for improving the performance of FSO systems by exploiting machine learning. There are several other seminal papers dealing with other specific aspects. We first present the spectrum of FSO communication, followed by the main obstructive factors that reduce the system quality, and finally provide a brief description of some proposed methods to improve the overall reliability of FSOs.

V. References

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