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# Deep Learning for channel estimation in FSO communication system

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ABSTRACT

Perfect channel estimation is a complex task with high power consumption and cost; in addition, requiring pilot transmission reduces the data rate. So, it is not favourable especially in mobile communication systems. The aim of this paper is to design (a new, low cost and low complexity) deep learning based channel estimator for free space optical (FSO) communication. In order to have a better understanding, this paper goes deeper through the problem, and presents different new deep learning based FSO systems, in which deep learning is used as detector, joint constellation shaper and detector, channel estimator, joint channel estimator and detector, joint constellation shaper and channel estimator and detector. For comparison with conventional systems, the outstanding QAM modulation, perfect channel estimation and maximum likelihood detection is applied. Considering wide range of atmospheric turbulences, from weak to strong by Gamma–Gamma model, symbol error rate performance of the proposed structures is investigated. Results indicate that the proposed deep learning based channel estimation technique, despite its less complexity, cost and power consumption provides close enough performance to the perfect channel estimation. It should be noted that the proposed structure does not need pilot sequence, hence, it has higher data rate than perfect channel estimation. The performance of the proposed deep learning based structures does not change with atmospheric turbulence variation. Furthermore, they are low cost, low complexity, with favourable performance. Accordingly, they could be good choices especially for mobile communication systems. Because the transceiver of these systems is a small mobile phone that should have low cost, complexity, and power consuming.

## 1. Introduction

Free space optical (FSO) communication system, due to its advantages over conventional radio frequency systems, is one of the most promising technologies for far future communication services [1]. FSO is very effective for outdoor communication applications; it is suitable for long range communication (without any need for signal amplification or correction) [2]. Despite outdoor radio frequency communication links, in which eavesdropping is easy, FSO links are immune to eavesdropping [3]. Aside these advantages, the outdoor atmospheric turbulence significantly degrades performance of FSO link, and limits its practical applications [4]. Accordingly, estimating the atmospheric turbulence channel (and consequently equalizing it) could really improve performance of FSO link. The outstanding conventional solution for this problem is perfect channel estimation, which is based on pilot transmission. However, perfect channel [5] estimation has high complexity and reduces data rate; in addition, it assumes that the channel is fixed for the duration between two consequence transmitted pilots. Blind channel estimation [6,7] requires lower complexity and does not need pilot transmission, but it assumes that the channel is fixed for the duration of some transiting symbols, which in fact is not a realistic assumption. These problems in conventional systems bring the question to the mind that is there any solution for obtaining a low complexity favourable estimation of realistic channel conditions?

Recently, machine learning [8] attracted many considerations in optical communication investigations. Machine learning is very useful in situations that the system model is not available (e.g. fibre optic channel) or is complex (channel with interference). Applying machine learning algorithms such as support vector machine [9], and neural network [10], is shown to be really helpful for reducing computational complexity in various optical communication tasks. In the training phase, machine learns the structure of the data and finds the relation between input and output (learns how to do its assigned task). However, when the relation between input and output is very complex or when the input is not enough, it is required to learn deeper. Deep learning [11] by consuming more complexity, could solve complex problems favourably. It offers powerful statistical signal processing tools that could learn the received data impairments and generate an accurate probabilistic model for impairments. Deep learning is an extended

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form of neural network and includes many algorithms such as deep neural network (DNN) [12], conventional neural network [13]. DNN first learns the model of the signal/system behaviour from the input data, and can be used in high-level simulation and design, providing fast responses. DNN learns the input–output data relationship by using several layers of connected neurons; each connection has a weight that represent its importance. DNN is more flexible than other deep learning algorithms and could be used for various applications, such as mitigating the fibre effects [14], modulation format identification [15], optical performance monitoring [16], optical amplifier control [17], as well as some optical network applications [18,19]. For more information about the applications of machine/ deep learning on optical communication, might be useful.

Despite huge amount of investigations in machine learning for optical communication, few works are done in machine learning for FSO communication. These works applied machine learning algorithms for detection [20], distortion correction for sensor-less adaptive optics [21,22], and demodulator for orbital angular momentum beams [23–26]. So, FSO is a free field for machine learning investigation, and according to the increasing rate of machine learning for optical/wireless communication instigations, it is expected that machine learning for FSO communication becomes a hot topic in the next few years. The purpose of this paper is to present a new channel estimation technique for FSO communication system. The proposed deep learning based channel estimator is cheap and low complexity; it does not need pilot sequence (so it has higher speed than perfect channel estimation); (despite perfect/blind channel estimation) it does not need to be used only for channels that are fixed for the duration of some symbols. In order to have a comprehensive investigation, this paper presents five new FSO communication systems, in which deep learning is used as channel estimator, detector, joint constellation shaper and detector, joint channel estimator and detector, joint constellation shaper, channel estimator and detector. To the best of the author's knowledge, novelties of this paper include: Presenting several new deep learning based FSO communication systems, and presenting several new applications of deep learning in FSO communication system, including constellation shaping, channel estimation, and detection. Considering Gamma–Gamma atmospheric turbulence (weak to strong regimes), symbol error rate of the proposed structures is compared with each other and with the outstanding conventional system, which is composed of QAM modulator, perfect channel estimator and maximum likelihood detector. The reason for using DNN in the proposed structures is that the DNN is the only machine learning algorithm that could be applied anywhere (constellation shaper, channel estimator, and detector), in any type (supervised, and unsupervised). For example, even support vector machine (which is a supervised binary classifier), despite its favourable performance in detection, could not be applied in other parts such as constipation shaper or channel estimator (because these two parts are unsupervised). So, for reasonable comparison between DNN and support vector machine, they should be applied as a supervised detector. In the results section this comparison is also done. DNN is the most widely used deep learning technique in optical communication, and is an appropriate alternative to conventional methods. DNN has low complexity and its response is fast; it can model complex multi-dimensional nonlinear relationships. Due to these advantages, applying DNN in FSO for constellation shaping, channel estimation, and detection, could significantly reduce complexity, cost, latency, and processing, while maintaining performance of the system.

The rest of this paper is organized as follows; in Section 2 the proposed system models are presented in details, Section 3 is the results and discussions of comparison between the proposed structures, and Section 4 is conclusion of this work.

## 2. System model

Each subsection of this section is devoted to one of the proposed structures (of Fig. 1). For the sake of simplicity and understandability, the name of each subsection is composed of three parts, the first part indicates the constellation shaper (QAM or DNN), the second part indicates the channel estimator (perfect channel estimation or DNN), and the last part indicates the detector (maximum likelihood or DNN).

### 2.1. QAM-perfect channel estimation-maximum likelihood

The first structure (see Fig. 1a) is a pure conventional structure, which is composed of QAM modulation, perfect channel estimation, and maximum likelihood detection. This system is considered in order to be compared with the proposed deep learning based structures. As is depicted in Fig. 1, the information signal is transmitted by an optical transmitter and received by a coherent optical receiver. Considering $x$, as the transmitted FSO signal, the received signal at the receiver aperture can be expressed as:

$$y = RIx + n, \tag{1}$$

where $n$ is the receive aperture input additive white Gaussian noise (AWGN) with zero mean and $\sigma^2$ variance; $I$ is the atmospheric turbulence intensity, which is assumed to be Gamma–Gamma; $R$ is photo detector responsibility. The background noise limited receivers in which the shot noise created by background radiation is dominant compared to other noise components such as thermal noise, dark noise, and signal-dependent shot noise. Therefore, the noise term is modelled as signal-independent AWGN [27]. Assuming perfect channel estimation, the maximum likelihood receiver becomes as follows:

$$\hat{x}_u = \underset{\tilde{x}_u}{min} \left| y - RI\tilde{x}_u \right|^2, \tag{2}$$

where $\tilde{x}_u$ is a symbol of the transmitted constellation map.

### 2.2. QAM-perfect channel estimation-DNN

In the second structure (Fig. 1b), deep learning is used for detection, and is composed of QAM modulation, perfect channel estimation and DNN based detection. Consider $x$ as the transmitted symbol, this symbol is first converted to a one-hot vector (because at the end, the output of the DNN would be a vector with size $M$, which is wanted to be the same as this one-hot vector). Then the one-hot vector is mapped on an M-QAM constellation and transmitted from FSO transmitter, passed though the atmospheric turbulence, and received at a FSO receiver. The received signal is complex, but DNN does not accept complex numbers; so, its real and imaginary parts are separated and entered a DNN with 2 input neurons, $M$ output neurons, $N_{hid}$ hidden layers, $N_{neu}$ per layer neurons, $\alpha(.)$ activation function, $\boldsymbol{W}$ weight matrix, and $\boldsymbol{b}$ bias vector. The purpose is to adjust DNN parameters (weight and bias) such that the receiver could better recover the original transmitted M-ary symbol. in other words, the DNN output be the same as the one-hot vector at the transmitter.

In order to solve this problem efficiently, the DNN should be trained. The first step in training a DNN is selecting and tuning its hyperparameters. The DNN hyperparameters include sample size to batch size ratio, layer type, number of layers, number of neurons, activation function, loss function, optimizer, learning rate, and number of iterations. Sample size to batch size ratio is important because entering the whole data at once into the DNN leads to underfitting while dividing it into several batches helps DNN to better understand the data structure. The number of layers, as well as neurons, should be adjusted by trial and test, and there is no specific rule for tuning them. There is a complexity-accuracy tradeoff between different activation functions, however some of them such as tanh, sigmoid, relu are shown to be proper for deep learning for optical communication tasks. For more information about hyperparameter tuning, is recommended.

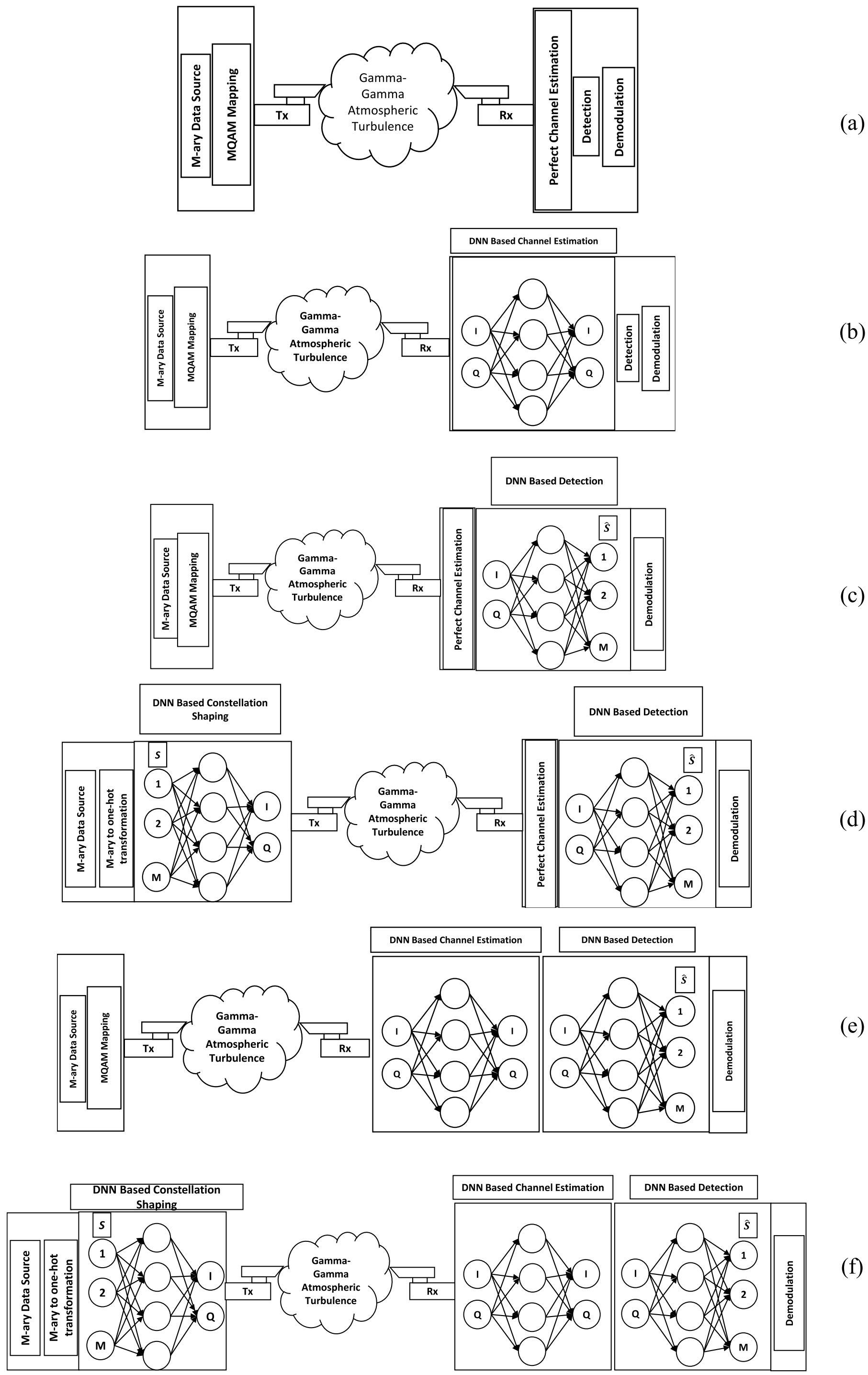


**Fig. 1.** a. the outstanding conventional FSO communication system, and the proposed FSO communication systems in which DNN is used as b. channel estimator, c. detector, d. joint constellation shaper and detector, e. joint channel estimator and detector, f. joint constellation shaper, channel estimator and detector.

The inputs of each layer of DNN are multiplied by weights, added by biases, summed, and entered an activation function. The outputs of each activation function are the inputs of the next layer, and the same procedure continues until the end of the DNN. Considering the one-hot vector (at the transmitter) as $s$ and the output vector of the DNN as $\hat{s}$, the aim is to reduce the difference between $s$ and $\hat{s}$. Therefore, a loss function should be defined and calculated for each individual transmitted symbol and expected over the whole batch size.

The proposed loss function could be defined as [28]:

$$L(\theta) = \frac{1}{K}\sum_{k=1}^{K}\left[l^{(k)}(\boldsymbol{s}, \hat{\boldsymbol{s}})\right] \tag{3}$$

where $\theta$ is the DNN parameters (including weight and bias vectors), $K$ is the batch size, $l(.,.)$ is loss function. The considered loss function is the cross-entropy, defined as [28]:

$$l(\boldsymbol{s}, \hat{\boldsymbol{s}}) = -\sum_{i} s_i log(\hat{s}_i). \tag{4}$$

Several algorithms have been proposed for minimizing the loss function by adjusting $\theta$. One of the most popular algorithms is stochastic gradient descent (SGD) which adjusts $\theta$ iteratively in the following manner [28];

$$\theta^{(m+1)} = \theta^{(m)} - \eta \nabla_{\boldsymbol{\theta}} \tilde{L}\left(\theta^{(m)}\right) \tag{5}$$

where $\eta > 0$ is the learning rate, $m$ is the iteration number, and $\nabla_{\theta} \tilde{L}(.)$ is the gradient of the loss function estimate (which is fed back to the DNN as an updating guide). Optimization is a tricky subject, which depends on the input data quality and quantity, model size, and the contents of the weight matrix. Stochastic Gradient Descent methods could be used for determining update direction and solving (5) [28]. As the state of-the-art algorithm with enhanced convergence, the Adam algorithm is used for optimization during the training process in this work. All numerical results in the manuscript have been generated using the deep learning library TensorFlow.

**Table 1**
Tuned hyperparameters.

| Hyperparameter | Value |
|---|---|
| Modulation order | 16 |
| Number of hidden layers | 4 |
| Number of per layer neurons | 40 |
| Batch size | 2^16 |
| Sample size to batch size ratio | 4 |
| Number of iterations | 1000 |
| Activation function | Relu |
| Loss | Softmax cross entropy |
| Optimizer | Adam |
| Learning rate | 0.005 |
| Gamma–Gamma atmospheric turbulence intensity | Strong ($\alpha = 4.2, \beta = 1.4$)<br>Moderate ($\alpha = 4, \beta = 1.9$)<br>Weak ($\alpha = 11.6, \beta = 10.1$) |
| Photo detector responsibility | R = 1 |

### *2.3. DNN- perfect channel estimation-DNN*

The purpose of the third structure (Fig. 1c) is to investigate the effect of using DNN as joint detector and constellation shaper; therefore, it is composed of DNN based constellation shaping, perfect channel estimation, and DNN based detection. Consider $x$ as the generated M-ary symbol, it is first converted to a one-hot vector, then entered a DNN with $M$ input and 2 output neurons. For simplicity, and without loss of generality, other DNN structure is exactly the same as the DNN in Section 2.1. Complex summation of the DNN output results in a complex number which stands for the location of the transmitted symbol in the signal constellation. Actually, this DNN is used for constellation shaping, which is a solution for reducing the effect of atmospheric turbulence. Then the mapped symbol is transmitted, encountered by Gamma–Gamma atmospheric turbulence, and added by AWGN with zero mean and $\sigma^2$ variance. The received signal is entered a DNN exactly the same as the DNN of Section 2.2. The aim is to adjust the DNN parameters of the proposed structure simultaneously to reduce atmospheric turbulence effect, and recover signal better. The training procedure is exactly the same as descriptions of Section 2.2.

### *2.4. QAM-DNN-maximum likelihood*

The purpose of the fourth structure (Fig. 1d) is presenting a DNN based channel estimator. This structure is composed of QAM modulator, DNN based channel estimation, and maximum likelihood detector. Considering $x$, as the transmitted symbol, the received signal at the receiver is entered a DNN with 2 input and 2 output neurons, $N_{hid}$ hidden layers, $N_{neu}$ per layer neurons, $\alpha(.)$ activation function, $\boldsymbol{W}$ weight matrix, and $\boldsymbol{b}$ bias vector, actually the output of this DNN is the estimation of channel (which is done without any pilot symbols, and the channel is assumed to be un-correlated and stochastic). The received signal is entered a maximum likelihood detector, and by the use of the estimated channel, the transmitted signal is recovered. The aim is to adjust the DNN parameters of the proposed structure simultaneously to reduce atmospheric turbulence effect, and recover signal better. The training procedure is exactly the same as descriptions of Section 2.2.

### *2.5. QAM-DNN-DNN*

The purpose of the fifth structure (Fig. 1e) is to investigate the effect of using DNN for joint channel estimation and detection. This structure includes QAM modulation, DNN based channel estimation, and DNN based detection. Consider $x$ as the transmitted symbol, this symbol is first converted to a one-hot vector, then mapped on an M-QAM constellation, and transmitted through FSO channel. The transmitted signal is encountered by Gamma–Gamma atmospheric turbulence channel, and the receiver noise is added to the detected photocurrent of the photo detector. The received signal is first entered a DNN with the same structure as Section 2.4, the output of this DNN is the channel estimation, then considering this channel estimation for removing the effect of channel, the signal (with removed channel effects) is entered a DNN with the same structure as Section 2.2. The aim is to adjust the DNN parameters of the proposed structure simultaneously to reduce atmospheric turbulence effect, and recover signal better. The training procedure is exactly the same as descriptions of Section 2.2.

### *2.6. DNN-DNN-DNN*

The purpose of the sixth structure (Fig. 1f) is to investigate the effect of using DNN for joint constellation shaping, channel estimation, and detection, accordingly all of these parts are DNN based. Consider $x$ as the generated M-ary symbol, it is first converted to a one-hot vector, then entered a DNN with the same as the DNN in Section 2.3. Then the mapped symbol is transmitted, encountered by Gamma–Gamma atmospheric turbulence, and added by AWGN with zero mean and $\sigma^2$ variance. The received signal is first entered a DNN with the same structure as Section 2.4, the output of this DNN is the channel estimation, then considering this channel estimation for removing the effect of channel, the signal (with removed channel effects) is entered a DNN with the same structure as Section 2.2. The aim is to adjust the DNN parameters of the proposed structure simultaneously to reduce atmospheric turbulence effect, and recover signal better. The training procedure is exactly the same as descriptions of Section 2.2.

## 3. Results and discussions

In this section, the simulation results of performance of the proposed structures are compared. Simulations are done in Python, Tensorflow environment. The hyperparameters are tuned manually (Table 1), and based on previous knowledge from literature. Considering FSO link in Gamma–Gamma atmospheric turbulence, strong ($\alpha = 4.2, \beta = 1.4$), moderate ($\alpha = 4, \beta = 1.9$), and weak ($\alpha = 11.6, \beta = 10.1$) regimes are considered in the simulations. The hyperparameter tuning here is done manually, but the proposed DNN based structures could achieve the performance of the state of the art conventional systems (in perfect channel estimation) or get close enough to the ideal results (in DNN channel estimator). Although hyperparameter tuning improves performance, the achieved improvements are not so much considerable that deserve adding complexity and processing to achieve them. In addition, it is complicated, and time and power consuming, so, the manual tuning here might not be a bad idea.

In Fig. 2 symbol error rates (SER) of the proposed structures is plotted as a function of Es/N0 for a. weak, b. moderate, and c. strong atmospheric turbulence regime, when modulation order is $M = 16$. The aim of this paper is to investigate the effect of using DNN as a channel estimator at various system and channel models, and this aim is displayed in Fig. 2 as can be seen, when perfect channel estimation

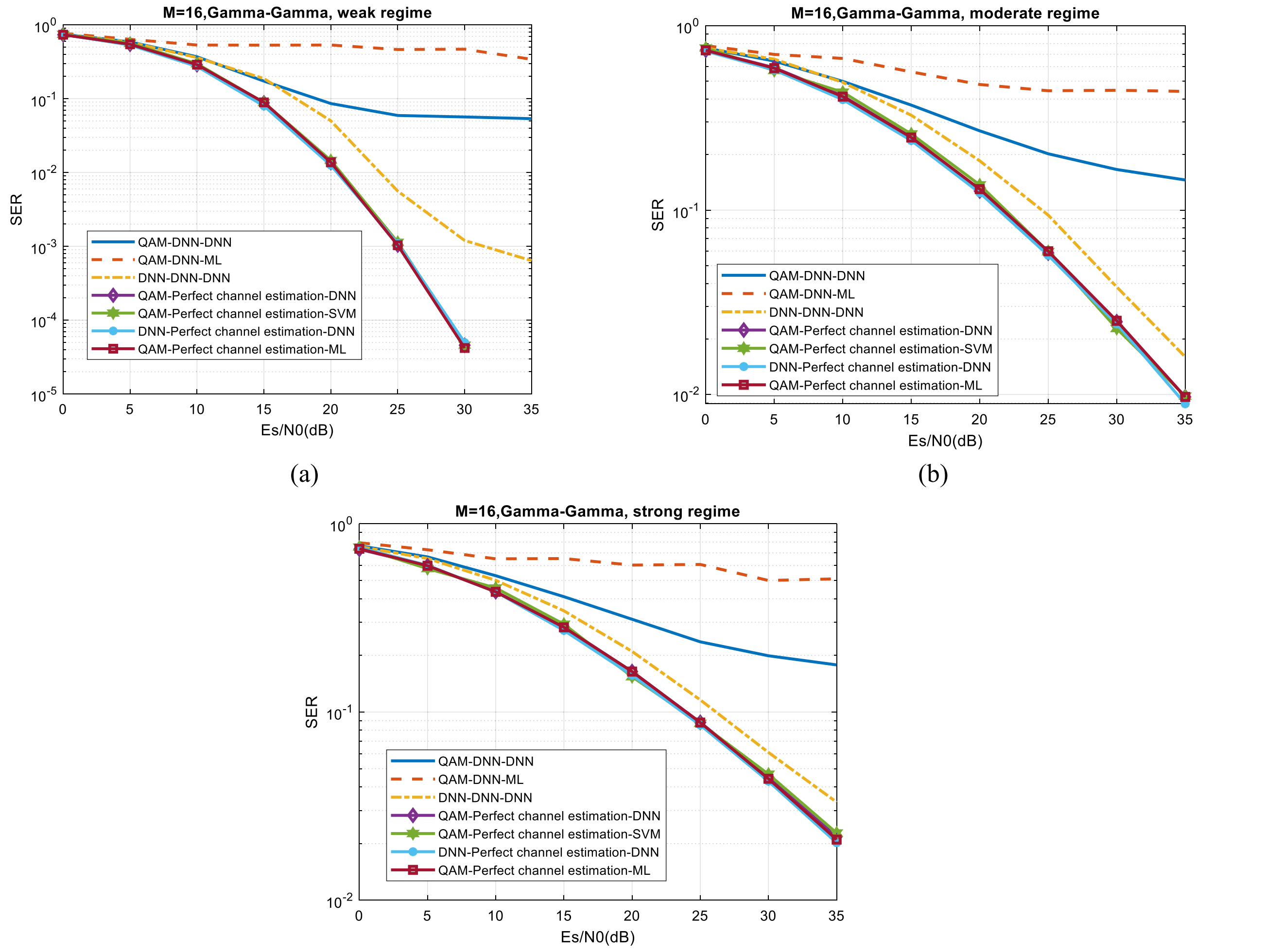


**Fig. 2.** SER of the proposed structures as a function of Es/N0 for a. weak, b. moderate, and c. strong atmospheric turbulence regime, when modulation order is $M = 16$.

is done, the effect of conventional and DNN based structures are the same, this is because when channel estimation is perfect, the problem that the DNN should solve is linear; actually, DNN outperformance over conventional systems is anywhere that model is not known or is non-linear. This shows that the proposed DNN based receiver does its work perfectly and efficiently in linear models. As can be seen, when channel estimation is not perfect, addition of each DNN system (detector, constellation shaper, and channel estimator), would improve performance of the system, because estimation of channel, when it is uncorrelated and stochastic is very hard without pilot symbol sequence, and this is exactly where DNN could be used. The performance difference between DNNs at each of these parts indicates that despite most of the applied investigations, which used DNN at the receiver side, DNN could be used as each parts of the communication system. Another thing that could be discussed is the difference between DNN based and conventional structures; as could be seen, this difference is almost the same for the all atmospheric turbulence regimes. So this is one of the advantages of the DNN based structures, immunity to the atmospheric turbulence variations makes this structure reliable. It is only tune and train it one time, it is expected to be robust at all atmospheric turbulence regimes. This reduces the cost and complexity required for running different systems for different atmospheric turbulence scenarios.

However, Fig. 2 (also) clearly compares support vector machine and DNN (when they are used both as detector). Actually, SVM is a binary classifier, so, it could only be used as the detector in a FSO communication system. Because, (e.g.,) the purpose of channel estimator or constellation shaper is not classifying anything (they are just predictors). SVM is a supervised machine learning algorithm, and needs labels in addition to features; in this system model, labels are only available at the detector, in the sense that the machine algorithm for constellation shaper and channel estimator should be unsupervised, and there is no label available for them. But DNN is everything, it is a supervised/un-supervised/semi-supervised/(and even) reinforcement machine learning algorithm. DNN could be used everywhere, because of its structure, it is the most flexible machine learning algorithm. That is why the works which used machine learning at the transmitter, used DNN. As can be seen, they have the same performance, (and both can achieve the maximum likelihood performance). This is because the model of FSO system is known and linear, and therefore, the optimum detector is available for it (the maximum likelihood), accordingly, when apply support vector machine or DNN as the detector, the actually find (and achieve) the optimum detector, and technically they do not outperform it.

Fig. 3 shows the proposed system models; the constellation maps for transmitter and receiver (under the proposed schemes) are shown in left and right columns, respectively. The system parameter details of these plots are explained in Table 1. The assumed Es/N0 is 10 dB. As can be seen, the transceiver constellations in cases without constellation shaping are the same, in cases with deep learning based joint constellation shaping, detection, and deep learning based joint constellation shaping, channel estimation, detection, the transceiver constellations are different, from Fig. 2, it can be concluded that (as is expected) the second deep learning based technique performs better.

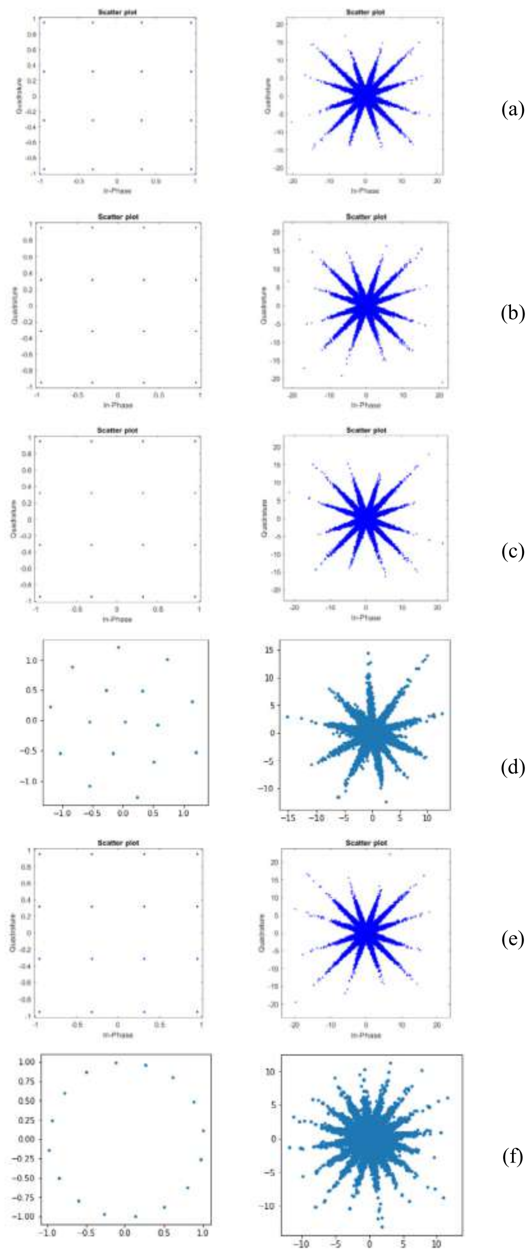


**Fig. 3.** (left column: Transmitted signal constellation, and right column: received signal constellation), a. the outstanding conventional FSO communication system, and the proposed FSO communication systems in which DNN is used as b. channel estimator, c. detector, d. joint constellation shaper and detector, e. joint channel estimator and detector, f. joint constellation shaper, channel estimator and detector.

## 4. Conclusion

Perfect channel estimation is a complex task with high power consumption, low data rate, and high cost. So, it is not recommended especially in mobile communication systems. The aim of this paper is to design the first deep learning based channel estimator for free space optical communication. In order to have a better understanding, different new deep learning based FSO systems are presented, in which deep learning is used as detector, joint constellation shaper and detector, channel estimator, joint channel estimator and detector, joint constellation shaper and channel estimator and detector. For comparison with conventional systems, the outstanding QAM modulation, perfect channel estimation and maximum likelihood detection is applied. Considering wide range of atmospheric turbulences, symbol error rate performance of the proposed structures is investigated. Results indicate that the proposed deep learning based channel estimation technique could get close enough to the perfect channel estimation. The performance of the proposed deep learning based structures does not change with atmospheric turbulence variation, and accordingly to the achieved performances, they could be good choices especially for mobile communication systems.

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