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Deep learning based channel estimation optimization in VLC systems

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Abstract

This paper aims to improve the channel estimation (CE) in the indoor visible light communication system. The proposal of this paper deals with a system that depends on a comparison between Deep Neural Network (DNN), Yolo v3, and Kalman filter (KF) algorithm, for two optical modulation techniques; asymmetrically clipped optical-orthogonal frequency-division multiplexing (ACO-OFDM) and direct current optical-orthogonal frequency division multiplexing (DCO-OFDM). The CE can be evaluated by the error rates in the received bits, where increased error means a performance decrease of the system and vice versa. Receiving less errors at the receiver indicates improved CE and system performance. Hence, the main aim of our work is to decrease the error rate by using different estimators. Furthermore, we apply automatic hyper-parameter approach and Bayesian optimization, to Yolo v3 model to improve the system performance and reduce the positioning error. The metric parameter of bit error rate (BER) aims to determine the improvement ratio in different systems. The model in this paper is based on training with OFDM samples of signal with labels which are received and are corresponding to the signals of OFDM. At a BER $= 10^{-3}$ with DCO-OFDM, the DNN outperforms KF with 1.7 dB (8.09%) at the bit energy per noise (E_b/N_o) axis. Also, for ACO-OFDM at BER $= 10^{-3}$, the DNN achieves better results than KF by about 1.9 dB (11.8%) at the (E_b/N_o) axis. For different values of M in QAM, the DNN outperforms KF for ACO-OFDM by average improvement of ~ 1.2 dB (~ 13%).

Keywords Neural network · Visible light communication (VLC) · Kalman filer (KF) · Direct current optical · Orthogonal frequency division multiplexing (DCO-OFDM) · Assymetrical clipping optical · Orthogonal frequency division multiplexing (ACO-OFDM)

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1 Introduction

Visible light communication (VLC) is important and is deployed in two fields, illumination and communication. Pulse width modulation (PWM), pulse position modulation (PPM), on–off keying (OOK), and OFDM schemes are some of the modulation techniques utilized in VLC systems (Aly 2021). The optical transmission data through channel is represented as a power and so, it cannot have any negative values. To grantee this issue, OFDM based on DCO and ACO techniques is used in our work. To evaluate the CE performance in indoor VLC system, both of BER and (E_b/N_o) are used. The KF has a huge role in different applications, as CE (Shawky et al. 2018; El-Shimy et al. 2018), positioning and localization systems (Shawky et al. 2020; Shawky 2021). Authors in Shawky et al. (2018) and El-Shimy et al. (2018) compared between KF, least square (LS) and minimum mean square error (MMSE) methods using two modulation techniques, ACO-OFDM and DCO-OFDM, where KF outperforms both LS and MMSE. Also, using ACO-OFDM decresed the BER than that done in DCO-OFDM. In Bektas and Panayirci (2021), channel sparsity exploited the DCO-OFDM for indoor VLC systems with a clipping noise. The simulation results showed that the algorithm converges in a maximum of two iterations and that gets excellent MSE and BER performance, outperforming CE algorithms, having no clipping noise mitigation capability. In Miao et al. (2021), the equalization scheme of the deep learning is applied in different channel impairments. The authors used two subnets to substitute modulation stage for leaning the nonlinearity of channel with the demapping symbols which are related to the training data. The obtained results showed that the proposed system addresses the overall channel impairments more efficiently and recovers the original symbols with improved BER performance. In Wu et al. (2020), deep learning technology is introduced for VLC systems in the CE scheme which depends on DNN. The aim of using DNN is to apply with few number of pilots the CE. The results validated the feasibility of DNN-based CE.

There are several methods for deep learninhg, e.g., CE (Wu et al. 2020), CSI-based positioning (Wang et al. 2016), and channel equalization (Chen et al. 1990). Zhang et al. (2018) used neural network (FFDNet) which depends on m-MIMO for CE in a VLC system for fast fading channel as 2D image. A hyper-parameter (HP) is a parameter in machine learning that must be fixed before the training process begins. As a result, unlike the value of parameters (e.g., weights) that may be taught during the training process, HPs (e.g., learning rate, batch size, and number of hidden nodes) cannot be learned during the learning process. HPs can affect the quality of the model produced by the training process as well as the algorithm time and memory requirements (Mai et al. 2019). As a result, HPs must be fine-tuned to provide the best results for a given situation. This fine-tuning can be done by hand or automatically. In automatic HP tweaking, a number of popular approaches are utilized. These include Bayesian optimization which is defined as a contrast to grid or random search. It selects the most promising HP values using a probability model of the objective function (Mai et al. 2019).

In a previous work Salama et al. (2022), performed a comparison between two modulation techniques; ACO-OFDM and DCO-OFDM, by using three different estimators LS, MMSE and KF. We used the DNN model to enhance the deep learning. In this paper, our proposal utilizes Yolo v3 with hyper-parameter (HP) model to optimize the channel estimation for CE with both DCO-OFDM and ACO-OFDM modulation schemes applied in deep learning model. The BER is used to assess performance. The findings show that deep learning approaches could be used to learn and assess channel properties, develop a model to help recovering distorted signals, and replace standard CE. Moreover, HP approaches based on Bayesian optimization are applied to improve our frame work.

The remainder of this paper is arranged as follows. Section 2 describes both of DCO-OFDM and ACO-OFDM modulation techniques. The DNN algorithm is explained in Sect. 3. In Sect. 4, the system results are displayed and discussed. Finally, Sect. 5 summarizes and concludes the work.

2 System model

2.1 DCO-OFDM

DCO-OFDM is one type of modulation techniques of OFDM, where the input data stream is modulated using the quadrature amplitude modulation (QAM) technique. In addition, the Hermitian Symmetry (HS) (Shawky 2021) is used to get real values after QAM. For btainning a time domain signal, we use Inverse Fast Fourier transform (IFFT) with N subcarriers. For cancelling intersymbol interference (ISI), we use a cyclic prefix (CP) for each OFDM symbol. For getting non-negative signal, the DCO-OFDM technique uses DC bias. The signal is transmitted via the optical channel. At the receiver, a line of sight (LoS) received signal is detected by the photodiode.

Inverse operations of the transmitter are done at the receiver. First, remove DC bias and then remove the CP. The output of pilot signals is used to estimate the channel by different techniques. FFT is used to return back to frequency domain. The output of QAM demodulation is used to obtain the output bit stream. The CE step is applied to recover the transmitted data at the receiver. The estimation is based on the transmission of pilot symbols which are known at the receiver. It is then optimized. The DCO-OFDM block digram is shown in Fig. 1 (Salama et al. 2022).

2.2 ACO-OFDM

Both CP and IFFT are used to obtain non-negative symbols and to avoid ISI, Fig. 2 (Salama et al. 2022). The imaginary odd input data is used to produce odd and real output, This is used for clipping to remove the negative part of signal, that does not change its amplitude.

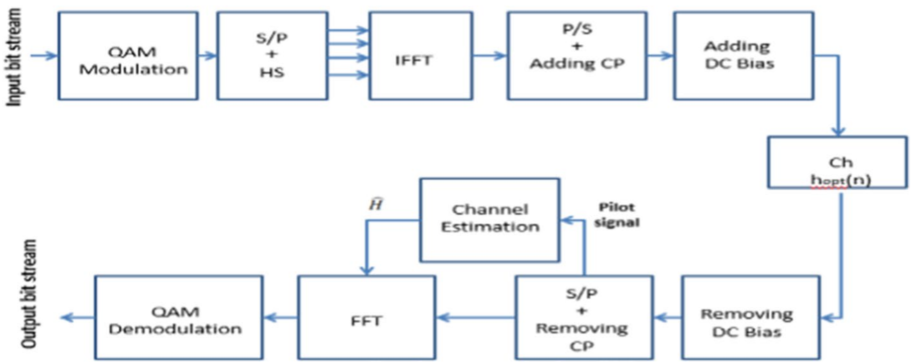


Fig. 1 Block diagram of the DCO-OFDM system (Salama et al. 2022)

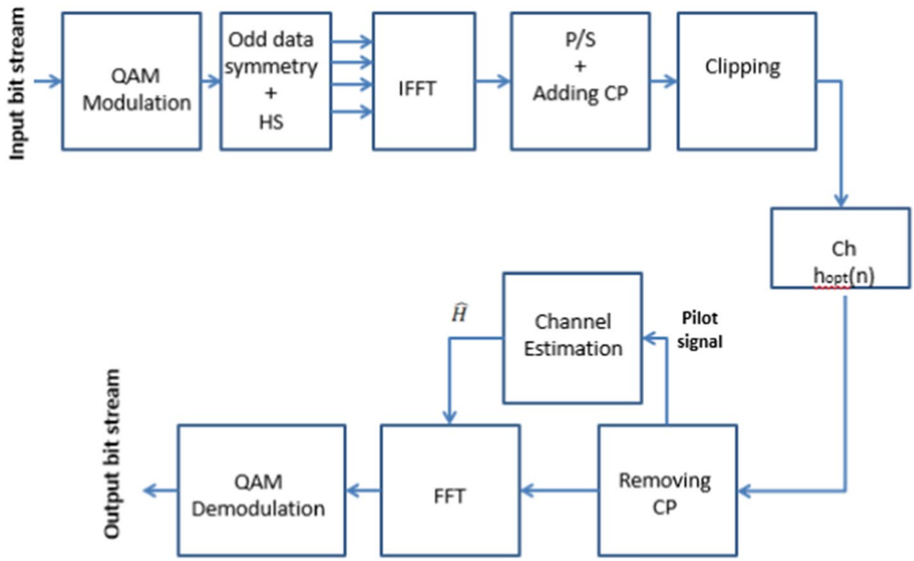


Fig. 2 Block diagram of the ACO-OFDM system (Salama et al. 2022)

A distortion is added in the part of imaginary for the subcarrier only (Qi Wang et al. 2015; Dissanayake and Armstrong 2013).

2.3 The algorithm for KF

The autoregressive (AR) model is applied to easily model the channel. In the KF, the channel coefficients h_k of the channel are modeled using the dynamic AR process (Shawky 2021)

$$h_{k+1,n} = \alpha_n h_{k,n} + v_{k,n} \quad (\mathrm{n} = 1, 2, 3, \ldots, \mathrm{N}) \tag{1}$$

where k represents the OFDM symbol, α_n is the time correlation of the channel response between kth and $(k+1)$th OFDM symbols at the nth sub-carrier, and $v_{k,n}$ is a Gaussian white noise.

First, consider only an AR model, where the channel response can be expressed as state x, as the following algorithm (Jain 2014; Wang and Chang 1996).

Predict step:

Predicted state estimate

$$\hat{x}_{k/k-1} = A_k \hat{h}_{k-1/k-1} + B_k u_k \tag{2}$$

Measurement equation:

$$z_k = h_k^T + v_k \tag{3}$$

Predicted estimate covariance

$$P_{k/k-1} = A_k P_{k-1/k-1} A_k^T + Q_k \tag{4}$$

Update step:

Compute Kalman gain as

$$K_k = P_{k/k-1} H_k^T (H_k P_{k/k-1}) \left(H_k^T + R_k\right)^{-1} \tag{5}$$

Updated estimate with z_k

$$\hat{x}_{k/k} = \hat{h}_{k/k-1} + K_k \left(z_k - H_k \hat{h}_{k/k-1}\right) \tag{6}$$

Updated the error covariance:

$$P_{k/k} = \left(I - K_k H_k\right) P_{k/k-1} \tag{7}$$

where X_k is the state estimate at (k). P_k is the error covariance matrix (a measure of the estimated accuracy of the state estimate). A_k is the state transition model. H_k is the observation model, Q_k is the covariance of the process noise, and R_k is the covariance of the observation noise.

3 Channel estimation DLM methods

The CE techniques are necessary for developing the recovery of the modulated signal. The following is a brief explanation for our proposed DNN model.

3.1 Yolo v3 with hyper-parameter optimization

As previously stated, the choice of HP affects the performance of a model, and determining the ideal value for each HP is not easy. As a result, we apply Bayesian optimization to adjust the suitable HP for the used Deep Learning Models (DLMs) to check if it brings any benefit. Both the Adam optimizer (Bock and Weiß 2017) and the Stochastic Gradient Descent (SGD) optimizer (Liu et al. 2020) were subjected to HP tuning. The best combination of Adam optimizer with Yolo v3 is a learning rate value of 0.001998, beta 1 value of 0.878 which gives a loss metric 2.23, Also, the best combination of SGD optimizer is a learning rate value of 0.01874, and a tuned momentum value of 0.985 which gives a loss metric of 1.99. Moreover, a batch size of 64 and a number of epoch 100 are obtained, for DLM. It is observed from our simulated work that the SDG optimizer is better than Adam optimizer in this datasets.

4 Results and discussion

According to the system models of ACO-OFDM and DCO-OFDM for indoor VLC system, Figs. 3 and 4, in simulations we use the KF algorithm and DNN model. In empty room with size $5 \times 5 \times 3$ m^3 for LOS channel response, an Additive White Gaussian Noise

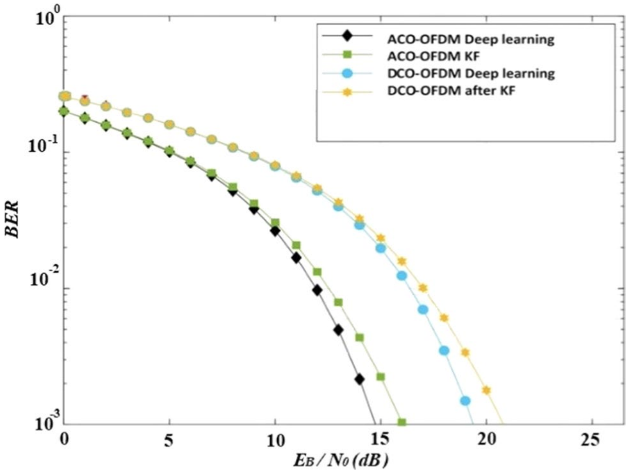
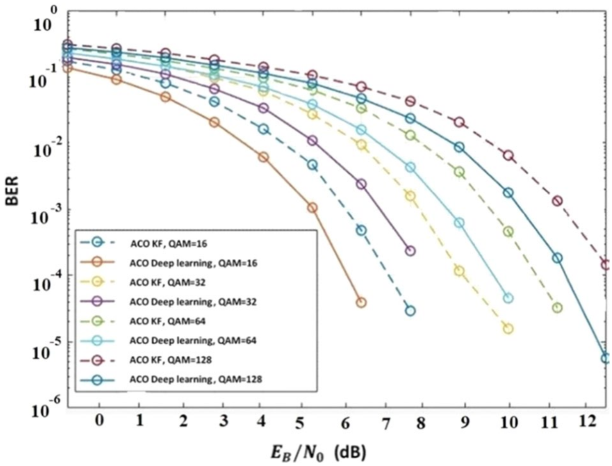


Fig. 3 Optimized BER performance for ACO-OFDM and DCO-OFDM

Fig. 4 Optimized BER using ACO-OFDM for M-QAM (M = 16, 32, 64, 128)



(AWGN) is added to the optical signal through the wireless channel. An LED is used in transmitter and a photodiode is used in receiver with air as an indoor optical channel.

Figure 3 illustrates the performance of the CE for both DNN and KF using ACO-OFDM and DCO-OFDM modulation techniques. Both BER and E_b/N_o are evaluating parameters the performance. When using 1024 OFDM subcarriers and M = 128 for QAM modulation, the results confirm that ACO-OFDM outperforms DCO-OFDM for both DNN and KF. The DNN achieves better results than KF for both ACO-OFDM and DCO-OFDM. At BER = 10^{-3} with ACO-OFDM, the DNN enhancement is 1.9 dB (11.8%) for E_b/N_o more than KF, and at BER = 10^{-3} with DCO-OFDM, DNN enhancement is 1.7 dB (8.09%) for E_b/N_o more than KF.

In Shawky (2021), there is a comparison between LS, MMSE and KF for different values of M and KF outperforms both of LS and MMSE. In our work, we perform a comparison between different values of the constellation M (16, 32, 64 and 128) for QAM

Table 1 Comparison between both KF and NN, with the optimized DNN model

Model	Enhancement percentage in BER	
KF with averaging (Shawky et al. 2018)	DCO-OFDM-KF	6.6%
	ACO-OFDM-KF	6.9%
NN (Salama et al. 2022)	DCO-OFDM-KF	7.6%
	ACO-OFDM-KF	8.12%
Optimized DNN (Present work)	DCO-OFDM-KF	8.09%
	ACO-OFDM-KF	11.8%

modulation between KF and DNN. Figure 4 illustrates this comparison for ACO-OFDM between DNN and KF. The DNN achieves better results than KF at different constellation values. At BER = 10^{-3}, there is an improvement for DNN over KF by ~ 1.2 dB (~ 13%) in E_b/N_o for M = 16, 32, 64 and 128.

Table 1 shows the comparison of the enhancement of the optimized DNN in the present work, with both NN model in Salama et al. (2022) and the KF in Shawky et al. (2018).

5 Conclusion

This paper aims to improve the CE using DNN and KF with different modulation techniques ACO-OFDM and DCO-OFDM. There is a positive relationship between improving the CE and decreasing BER that declares the importance of choosing BER as a metric parameter in the simulations. When comparing the optimzed DNN and KF for ACO-OFDM and DCO-OFDM, the DNN achieves better results over KF by about 11.8% and 8.09%, respectively. When using the QAM modulation technique with different values of M, again, the DNN outperforms KF for ACO-OFDM ~ 13%. The simulation results illustrate that Yolo v3 model outperforms other conventional estimators, and the optimization achieved an appreciable improvement by ~ 6 to 12% as compared to previous work.

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Declarations

Conflict of interest The authors declare that they have no conflict of interest.

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