Proceedings of CONF-SPML 2027 Symposium: Intelligent Network Security and Machine Learning for Communication Systems
DOI: 10.54254/2755-2721/2027.MELB37312

Deep Learning-Based Channel Equalization for Visible Light Communication Systems

Shixuan Kang

Glasgow College, University of Electronic Science and Technology of China, Chengdu, China
2024190905022@std.uestc.edu.cn

Abstract. Visible light communication (VLC) gets increasing attention with the continuous advancement of technology. In contrast to conventional wireless networks, VLC possesses numerous innovative advantages. It has an abundant optical spectrum with immunity to radio-frequency interference. More importantly, its compatibility with existing lighting infrastructure demonstrates its broad applicability. However, high-speed VLC systems still need to address numerous challenges during communication such as limited LED bandwidth, inter-symbol interference, device nonlinearity, and receiver noise. Due to the above-mentioned factors, the channel equalization becomes an important physical-layer function. This paper aims to clarify the strengths and limitations of different deep learning-based channel equalization methods with cross-method comparison. Meanwhile, finds suitable application scenarios for different VLC systems. This review explores neural-network architectures including artificial neural networks, convolutional neural networks, long short-term memory networks, and hybrid/model-driven structures. Finally, it also illustrates the importance of lightweight designs. The analysis shows that no single architecture is optimal for all VLC conditions. ANN is effective for nonlinear mapping, CNN is suitable for local feature extraction, while LSTM performs better for channel memory and inter-symbol interference.

Keywords: Visible Light Communication, Channel Equalization, Deep Learning, Neural Network, Nonlinear Compensation

1. Introduction

Visible light communication (VLC) is an emerging wireless technology that transmits information by rapidly modulating the intensity of light emitting diodes (LED), which can transform the light signal into a digital signal. Compared with conventional communication approaches, VLC is immune to radio-frequency interference and possesses abundant spectrum resources. This makes VLC more attractive among various communication approaches. To boost the communication data rate and exploit its full advantages, early works have attempted various methods including using practical LED hardware to support multi-gigabit transmission for VLC systems [1]. However, blindly increasing the transmission data rate also causes more severe impairments to physical-layer impairments. Numerous issues, such as limited LED bandwidth, inter-symbol interference(ISI),

DOI: 10.54254/2755-2721/2027.MELB37312

device nonlinearity, and receiver noise, can distort the received waveform which results in a reduction of communication reliability.

Therefore, channel equalization as a receiver function in high-speed VLC to solve relevant issues becomes more significant. For conventional equalizers remaining useful, their performance and computational cost can no longer cope with complex channel models. However, with the development of technology, deep learning provides a potential alternative because neural networks can learn complex nonlinear relationships directly from received samples. The diversity of neural networks also enables different models to adapt to various application scenarios. This paper therefore conducts a focused narrative review of representative learning-based VLC equalizers published over the past decade. Through literature analysis and cross-method comparison, the review examines the respective characteristics and limitations of ANN, CNN, LSTM, and hybrid/model-driven. Meanwhile, beyond neural network architectures, the importance of lightweight design is emphasized. This analysis aims to provide a clear reference for selecting practical VLC equalizers and identifying future research priorities.

2. VLC channel equalization fundamentals

2.1. Signal model and equalization objective

A simplified discrete-time representation can roughly present the intensity-modulation/direct-detection (IM/DD) link, which is

$$\mathrm{y}[\mathrm{k}] = (\mathrm{h} * \mathrm{x})[\mathrm{k}] + \mathrm{dNL}[\mathrm{k}] + \mathrm{n}[\mathrm{k}] \tag{1}$$

In this mainstream simplified model, every symbol has its meaning throughout the whole visible light communication process, where $\mathrm{x}[\mathrm{k}]$ is the transmitted waveform by the light signal, h and $\mathrm{dNL}[\mathrm{k}]$ denote the effective linear channel impulse response and nonlinear device distortion respectively, and $\mathrm{n}[\mathrm{k}]$ is noise, including the shot noise, thermal noise and even the ambient light interference. The received observations are not reliable data equal to the original expected information. So it is significant for the equalizer to estimate either the transmitted symbol or a compensated waveform of the one without distortion and noise from the transmitted symbol.

Equalization performance is commonly evaluated using several key indicators, including bit error rate (BER), error vector magnitude (EVM), Q-factor, or achievable transmission distance/rate. For learning-based receivers, those communication metrics should be considered together with parameter count, training requirements, and inference latency. For channel equalization in visible light communication, a good equalizer not only requires higher compensation capability but also needs to have an acceptable deployment cost.

2.2. Conventional baselines

For conventional equalizers, under the condition that the distortion is predominantly linear and the channel estimate is comparative reliable, these have higher efficiency, such as Linear FIR, zero-forcing, and MMSE equalizers. Meanwhile, to suit the significant nonlinear of LED, polynomial and Volterra-series models add nonlinear terms and memory. Li et al. showed that the traditional hybrid time-frequency-domain equalization can mitigate the significant effects induced by LED nonlinearity in OFDM-based visible light communication [2]. Zhang et al. formulated nonlinear equalization as a sparse-recovery problem, and these experiments showed that the matching-pursuit-

DOI: 10.54254/2755-2721/2027.MELB37312

based designs reduced the number of nonlinear kernels by 32.5%–62.5% for only a 0.5-dB SNR penalty [3]. These results illustrate the central trade-off that applies to equalizers that not only include the communication channel equalizers:It is most effective to improve compensation capability without compromising acceptable deployment cost.

3. Deep learning equalization architectures

3.1. Feed-forward ANN equalizers

The deep-learning model that was proposed early to potentially tackle nonlinear channel equalization is a feed-forward ANN equalizer. The underlying principle is to receive a short window of adjacent samples and get the mapping to an expected symbol or compensated sample. In channel equalization, feed-forward ANN equalizers were utilized as an effective means in early experiments to cope with device nonlinearity and the effective channel memory is modest. Such capabilities due to the nonlinearity within their hidden layer enable the fitting of complex transfer functions.

Early-stage experiments provide comparative information on the compensation capabilities of feed-forward ANN and conventional equalizers in visible-light communication (VLC). Haigh et al. provided one of the earliest experimental demonstrations: using a 4.5-MHz white LED and OOK modulation to compare the data rates under different equalizer configurations. In contrast to the lower data rates for decision-feedback, linear equalization, and no equalization, their ANN equalizer supported up to 170 Mb/s over the white spectrum [4]. The rates of traditional choices differ by a factor of two, four, or even eight with the ANN equalizer. The key conclusion is not the absolute rate because the hardware has advanced considerably since 2014, the ability of a learned nonlinear mapping can compensate for more information compared to traditional equalizers for the LED.

With the development of deep learning, ANN equalization is no longer limited to low-speed systems and can also be adapted to faster hardware. Subsequent emerging experimental studies have also validated this point. Wei et al. used an ANN equalizer to mitigate nonlinear effects in a single-pixel blue micro-LED QPSK-OFDM link and then demonstrated 8.75 Gb/s with a BER of 2.73×10^{-3} [5]. Channel memory can be incorporated by expanding the input window for an explicit long-term state, but this will come with the cost incurred by the increase in input dimension and weight count. Therefore, architectures that share weights or model temporal state more explicitly have thus emerged and undergone considerable development.

3.2. CNN and model-driven equalizers

CNN, owing to its shared kernels, can be better deployed in detecting local patterns in multiple scenarios. This mechanism offers stronger parallelism than recurrent networks and is well suitable to cause local waveform distortion by virtue of its capacity for local identification in time-domain samples, frequency-domain symbols, or engineered channel features. However, the temporal memory of a CNN is not infinite, which leads to certain limitations in capturing longer ones. Miao et al. use a conventional signal-processing structure with the neural module only for the specific task to propose a deep-learning receiver oriented toward indoor OFDM-VLC [6]. These tasks focused on nonlinear channel compensation and symbol demapping [6]. The model-driven philosophy provides an important insight because the conventional component can offer the known communication operations while the neural component can instead process the analytically difficult residual mapping. This philosophy can significantly improve computational efficiency by cutting the cost of relearning.

The limitation of a CNN is its finite receptive field, which decides the temporal memory. From a theoretical perspective, the amount of channel memory observed can be increased by broadening the kernel or deeper stack. Nevertheless, excessive broadening may also bring about the rise in computational cost, which diminishes the advantages brought by the model. Consequently, CNN is more effective for deployment in combining with feature engineering or recurrent modules.

3.3. LSTM and hybrid sequence equalizers

When symbols of different orders overlap in time, this causes the current observation to be erroneously influenced by previously transmitted symbols. This phenomenon is Inter-Symbol Interference(ISI) in the sequence. However, LSTM networks can mitigate the adverse effects brought by ISI during the equalization process because of their capability to maintain an internal state controlled with input, forget, and output gates. This theory has been validated in previous experiments, when Lu et al. innovatively designed a memory-controlled deep LSTM post-equalizer [5]. Using this experimental post-equalize assist the single-red-LED system in achieving 1.15Gb/s PAM4 and 0.9Gb/s PAM8 below the 3.8×10^{-3} HD-FEC threshold. This differed from the metrics obtained using FIR equalizer under the same hardware conditions. Experimental results show that Q-factor improvement was 1.2 dB and the transmission distance increased by one-third using LSTM post-equalizer [7]. This confirms that LSTMs are particularly well suited to channel memory tasks.

To preserve the temporal advantage brought by LSTM while improving reconstruction accuracy or interpretability, hybrid structures are built. In the previous experiment, Miao et al. tried constructing a hybrid structure by combining LSTM with a DNN refinement stage to formulate a memory-sequence prediction for visible light communication [8]. Tian et al. went further in VLC impairment compensation by using a CNN to extract impairment patterns and an LSTM to predict the memory sequence on the basis of constructing Volterra features [9]. These designs show a consistent trend that different modules in the equalizers are assigned different tasks instead of relying on only one type of deep network, this can improve the efficiency during the whole processing process.

3.4. Lightweight and complex-valued equalization

After we establish the architecture, the researches paid more attention to the model lightweighting as a key priority. This important goal is mainly achieved via increases of the parameter efficiency. Lu et al. once developed an equalizer that can effectively enhance parameter efficiency for QAM-CAP VLC [10]. A streamlined complex-valued extraction-and-fusion neural equalizer was proposed in this relevant research, which brought the shared extraction kernels and zero-overlap feature fusion. This design successfully reduced the parameter count by up to 49.2% while maintaining effective impairment compensation in experiments. Compared with the failure of other equalizers, this structure can still maintain a low bit-error rate under severe distortion [10]. This work is significant because it focuses on an open question: how to deploy appropriate structures upon it for bit-error-rate reduction once the architecture is established.

4. Cross-method comparison

Over recent years, numerous studies targeting VLC channel equalization have proposed a variety of equalizer architectures based on deep-learning neural networks. But different experimental projects produced considerable differences in hardware and signal formats because of different experimental

DOI: 10.54254/2755-2721/2027.MELB37312

projects. This is a key reason why people can not rank equalizers fairly only according to headline data rate in experimental results. To reflect the differences among various equalizers, comparisons at the architectural level are more meaningful. The features of different neural network architectures determine their application scenarios. Table 1 shows that the feed-forward ANN is relatively simple and parallelizable but relies on an explicit input window to represent memory. CNN benefit from parameter sharing and are efficient for local distortion compared to other architectures. However, long dependencies depend on the magnitude of receptive fields, which is bound to introduce certain limitations. LSTM explicitly models temporal causality, which is designed as sequence equalization for the effective solution of ISI. But this architecture can cause the limitation for throughput because of gate operations and sequential state updates in the course of practical deployment. Different neural networks and conventional signal-processing modules can be integrated into a hybrid architecture in which different types of tasks are assigned to specialized components. Such an architecture needs more careful design than others while reducing the burden on learned components in exchange.

Table 1. Qualitative architecture comparison

Architecture	Nonlinear Modeling	Temporal Memory	Parallelism	Typical Complexity	Best-Fit VLC Use
ANN	High	Low–Medium*	High	Low–Medium	Short-memory nonlinear compensation
CNN	High	Medium	High	Medium	Local waveform / OFDM feature distortion
LSTM	High	High	Low–Medium	Medium–High	ISI and sequence equalization
Hybrid / model-driven	High	High	Medium	Medium–High	Mixed impairments with prior knowledge

*A feed-forward ANN can represent memory by including multiple adjacent samples in its input window. The table is a qualitative synthesis of the reviewed architectures, not a universal ranking.

5. Conclusion

This review examined deep learning-based channel equalization for visible light communication systems, which conducts an in-depth comparison of the feature structures and applicable scenarios of different neural-network architectures. The comparison leads to the conclusion that there is no optimal architecture for VLC channel equalization. The different channel conditions are key decisions for the corresponding deep-learning architectures. Feed-forward artificial neural networks are effective for compact nonlinear mapping. And convolutional neural networks are useful for local waveform and frequency-domain feature extraction. Facing the inter-symbol interference and channels with temporal memory, long short-term memory networks are better choices. Hybrid and model-driven structures have the potential to continuously reduce the burden of learning components on the premise of careful design. Once the architecture is determined, moving toward lightweight design also helps improve equalization efficiency.

Nevertheless, the study targeting VLC channel equalization still suffers from numerous limitations. First, the analysis mainly focuses on the representative studies rather than an exhaustive literature search. Second, the results of different studies are not directly comparable due to various factors such as discrepancies in hardware platforms, modulation formats, channel conditions, and evaluation protocols. Furthermore, no hardware benchmark was available to quantitatively reevaluate the reviewed equalizers under identical conditions. Looking ahead, future research should therefore focus on standardized VLC datasets for realizing sufficiently precise horizontal comparisons. While investigating architectures, attention should also be paid to lightweight design and hardware implementation after architecture determination. Model-driven and hardware-aware deep learning may be especially valuable for achieving reliable equalization with lower latency, memory use, and computational cost.

References

[1] Bian, R., Tavakkolnia, I., & Haas, H. (2019). 15.73 Gb/s visible light communication with off-the-shelf LEDs. *Journal of Lightwave Technology, 37*(10), 2418–2424. https://doi.org/10.1109/JLT.2019.2906464

[2] Li, J., Huang, Z., Liu, X., & Ji, Y. (2015). Hybrid time-frequency domain equalization for LED nonlinearity mitigation in OFDM-based VLC systems. *Optics Express, 23*(1), 611–619. https://doi.org/10.1364/OE.23.000611

[3] Zhang, G., Hong, X., Fei, C., & Hong, X. (2019). Sparsity-aware nonlinear equalization with greedy algorithms for LED-based visible light communication systems. *Journal of Lightwave Technology, 37*(20), 5273–5281. https://doi.org/10.1109/JLT.2019.2931330

[4] Haigh, P. A., Ghassemlooy, Z., Rajbhandari, S., Papakonstantinou, I., & Popoola, W. (2014). Visible light communications: 170 Mb/s using an artificial neural network equalizer in a low bandwidth white light configuration. *Journal of Lightwave Technology, 32*(9), 1807–1813. https://doi.org/10.1109/JLT.2014.2314635

[5] Wei, Z., Liu, Z., Liu, X., Wang, L., Wang, L., Yu, C., & Fu, H. Y. (2021). 8.75 Gbps visible light communication link using an artificial neural network equalizer and a single-pixel blue micro-LED. *Optics Letters, 46*(18), 4670–4673. https://doi.org/10.1364/OL.437632

[6] Miao, P., Yin, W., Peng, H., & Yao, Y. (2021). Study of the performance of deep learning-based channel equalization for indoor visible light communication systems. *Photonics, 8*(10), Art. no. 453. doi: 10.3390/photonics8100453.

[7] Lu, X., Lu, C., Yu, W., Qiao, L., Liang, S., Lau, A. P. T., & Chi, N. (2019). Memory-controlled deep LSTM neural network post-equalizer used in high-speed PAM VLC system. *Optics Express, 27*(5), 7822–7833. doi: 10.1364/OE.27.007822.

[8] Miao, P., Chen, G., Cumanan, K., Yao, Y., & Chambers, J. A. (2022). Deep hybrid neural network-based channel equalization in visible light communication. *IEEE Communications Letters, 26*(7), 1593–1597. doi: 10.1109/LCOMM.2022.3172219.

[9] Tian, D., Miao, P., Peng, H., Yin, W., & Li, X. (2022). Volterra-aided neural network equalization for channel impairment compensation in visible light communication system. *Photonics, 9*(11), Art. no. 845. doi: 10.3390/photonics9110845.

[10] Lu, X., Li, J., Li, Y., Huang, T., Li, Y., & Liu, Y. (2025). Streamlined complex-valued neural network equalizer based on extraction and fusion technique in visible light communication. *Journal of Lightwave Technology, 43*(2), 579–588. doi: 10.1109/JLT.2024.346173.