Challenges and Prospects of Machine Learning in Visible Light Communication

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***Abstract*—Visible light communication (VLC) is a promising research field in modern wireless communication. VLC has its irreplaceable strength including rich spectrum resources, no electromagnetic disturbance, and high-security guarantee. However, VLC systems suffer from the non-linear effects that exist in almost every part of the system. As a part of artificial intelligence, machine learning (ML) is showing its potential in non-linear mitigating for its natural ability to fit all kinds of transfer functions, which may dramatically push the research in VLC. This paper introduces the application of ML in VLC, describes five recent research of deep learning applications in VLC, and analyses the performance.**

***Keywords*—visual light communication, machine learning, artificial intelligence, deep learning, neural network**

I. Introduction

Visible light communication (VLC) is an emerging wireless communication method that uses visible spectrum for communication[1]. As the wide promotion of light emitting diodes (LEDs), LEDs have attracted more and more attention from scholars due to the unique function of combining lighting and communication[2]. VLC has many advantages, including rich spectrum resources between 400∼800 THz, high anti-electromagnetic interference, and high confidentiality. In the field of underwater communication, VLC has become the best method to achieve the wireless communication with both high speed and long distance by now.

However, in many VLC research works, the transmitted signal always suffers from linear and nonlinear distortion, especially for the case with complex channel and high output signal power[3]. Nonlinear effect will strongly damage system performance and cause the rise of bit rate error. The nonlinear effect in VLC systems mainly comes from the nonlinear response of LEDs, channel, and the photodiode (PD) at the receiver[4,5]. Most of the current equalization scheme can only compensate some simple nonlinear effect without the ability to handle complex nonlinear effect.

Machine learning (ML) related algorithms have been successfully applied in prediction, classification, pattern identification and data mining, etc[6]. Firstly, many useful algorithms in ML have been demonstrated to solve some issues related to nonlinearity in optical communication field, such as estimating parameters from noise, determining the complex mapping relationship between input signal and output signal, inferring the probability distribution of received signals and estimating output values based on input samples, etc[6,7]. Secondly, ML algorithms can be utilized to monitor communication performance, such as neural network and K-means algorithm that can help estimate various channel impairments and manage optical network efficiently[8]. In addition, ML algorithms, such as support vector machine (SVM) and K-means algorithm, can accurately identify modulation formats and bit rate. Because machine learning algorithm can fit and model the relationship between inputs and outputs according to samples and labels without accurately analyzing the complex relation between each feature, ML algorithms are potential tools to be applied in VLC systems and improve their transmission performance.

In this paper, we will first introduce the structure of VLC systems and analyse some classical applications of ML techniques in VLC systems. Some recent contributions about deep neural networks (DNNs) are also given. Our goal is to assist the readers in refining the motivation, structure, performance and cost of some typical ML techniques for future VLC systems to tap into hitherto unexplored applications and services.

II. The Principle and the Mechanism of ML in VLC

A. The Architecture of ML Enhanced VLC System

The typical structure of an ML enhanced VLC system is illustrated in Fig. 1. The entire system can be divided into 5

Manuscript received May 05, 2020; revised Aug. 04, 2020; accepted Aug. 09, 2020. This work was partially supported by National Key Research and Development Program of China (2017YFB0403603) and the NSFC project (No.61925104). The associate editor coordinating the review of this paper and approving it for publication was C. Huang.

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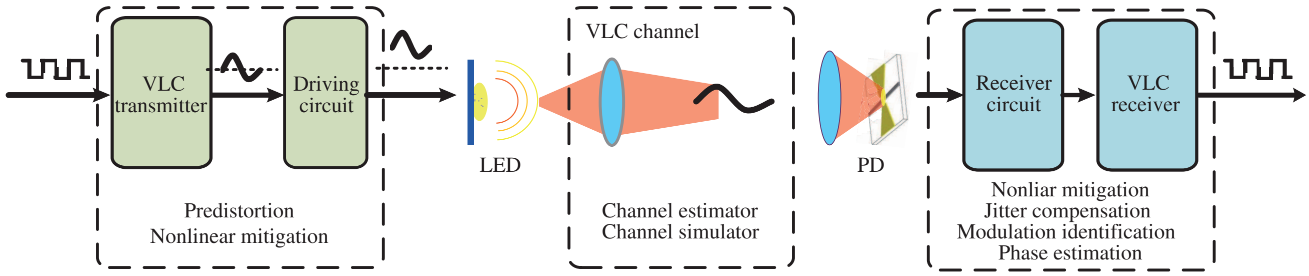

Figure 1 A machine learning enhanced VLC system

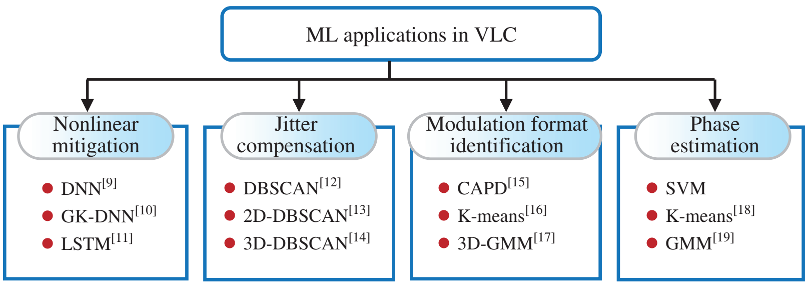

Figure 2 ML applications in VLC

parts by their function: the VLC transmitter, the driving circuit, the VLC channel, the receiver circuit, and the VLC receiver. The transmitter and the receiver are usually the ML enhanced parts.

The VLC transmitter covers the digital signal processing processes, including the coding of the transmitting binary data, the modulation, the pre-equalization if required, the up-conversion, and finally the generation of the digital signal that can be sent to the transmitter circuit.

The driving circuit consists of the arbitrary waveform generator (AWG), the electronic amplifier (EA), the hardware pre-equalizer, the bias tee, and of course the LED. The AWG finishes the task of converting the generated digital signal to the analogue signal; the hardware pre-equalizer broadens the usable bandwidth in the VLC system; the bias tee mixes the bipolar zero-mean signal with the direct current bias and thus drives the LED.

The channel in a VLC system can be either free space or underwater. The characteristic of the light attenuation through the channel is complicated, confusing the channel model and bringing the challenges in VLC systems.

The light with signal is collected by the receiver circuit, which includes the PD, the trans-impedance amplifier (TIA), the EA, the attenuator and the oscilloscope. The TIA amplifies the weak electrical signal converted from light by the PD together with the EA. The attenuator adjusts the amplitude of the amplified signal to fit the proper dynamic range of the oscilloscope, which acts as the analogue-to-digital converter.

The VLC receiver undertakes the digital signal processing at the receiver side with the help of a series of processes like the differential operation, the down-conversion, the post-equalization, the demodulation and finally the decoding. The decoded binary data stream can be used to calculate the bit-wise error rate, indicating the performance of the entire transmission system.

B. ML Applications in VLC

ML is a multidisciplinary cross-discipline involving statistics, probability, optimization theory, and algorithm complexity theory. As shown in Fig. 2, the application of ML in VLC can be divided into the following 4 categories.

• Nonlinear mitigation. Nonlinearity is a unique challenge in VLC, which exists almost everywhere in the VLC systems. The voltage-current (VI) characteristic of the emitting component, LED, is not linear, which means the power of the emitting light is not linear proportional to the controlling signal. Furthermore, the VLC channel is highly complicated. The nonlinearity in the VLC channel causes a severe fading both in the time domain and in the frequency domain. Last but not least, the receiving photoelectronic components, such as PD and avalanche PD, have a saturation effect that may cause the cutting of the receiving signal.

In recent years, artificial neural networks (ANNs) have been widely used in VLC systems to compensate for nonlinear damage of signals. By using a part of the transmitted signal as the label, the ANNs can learn the characteristics of the system through its powerful nonlinear mapping ability, thereby compensating for the nonlinear damage of the system. In Refs. [9-11], the utilization of DNNs in the faster-than-Nyquist VLC system, the implementation of Gaussian kernel

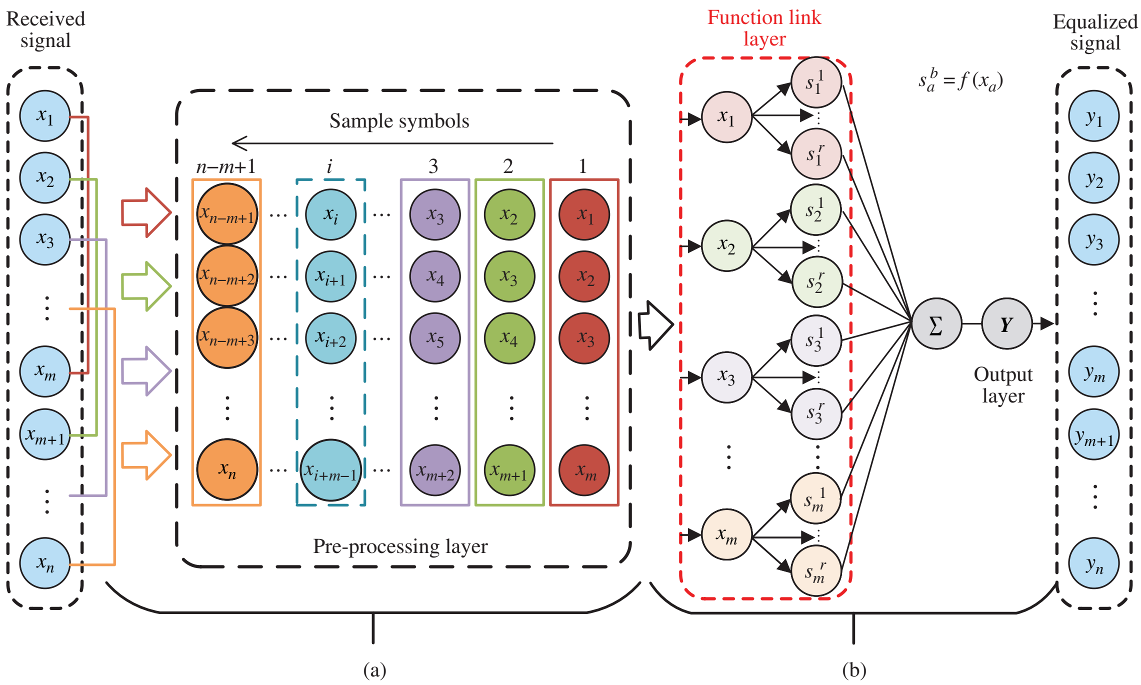

Figure 3 The schematic for (a) original data pre-processing; (b) general function link artificial neural networks

based DNN (GK-DNN) and long short-term memory (LSTM) in the phase-amplitude modulation (PAM) based VLC system have proved the superiorities of deep learning in nonlinear compensation.

- Jitter compensation. In VLC systems, the system jitter will cause signal distortion, and utilizing the traditional decision strategy will cause misjudgment of the signal. In Refs. [12-14], the authors use 2 dimensional density-based spatial clustering of applications with noise (2D-DBSCAN) and 3D-DBSCAN algorithms to blindly equalize PAM and quadrature amplitude modulation (QAM) signals, effectively eliminating false decisions caused by signal jitter and effectively improved system performance.
- Modulation format identification. The nonlinearity in VLC systems will cause a mismatch of constellation points, resulting in the misjudgement of the receiving signal. In Refs. [15,16], cluster algorithm of perception decisions (CAPD) can be generated by using K-means, thereby improving the performance of VLC systems. Similarly, in Ref. [17], the author uses Gaussian mixture model (GMM) to regenerate the decision boundary for QAM signals, which effectively alleviates the misjudgement caused by constellation mismatch.
- Phase estimation. In VLC systems, the nonlinearity will cause phase deviation in the receiving signal. By using ML algorithms such as SVM, K-means[18], and GMM[19], the nonlinear deterioration of the VLC systems caused by phase deviation can be effectively compensated.

With the substantial improvement of computer computing power and data storage capacity in recent years, the power of deep learning in dealing with nonlinear problems in communication systems has been widely explored. In this paper, we review the specific application of functional linked artificial neural network (FLANN), GK-DNN, dual-branch multilayer perception post-equalizer algorithm (DBMLP), and joint time-frequency post-equalizer deep neural network (TFDNet) in the VLC system to show the great potential of ML in VLC systems. These 5 applications have good performances on the nonlinear mitigation.

III. Deep Learning in VLC

A. Function Link Artificial Neural Network

There exists various linear and nonlinear noise in VLC systems, and an efficient equalizer is indispensable for high spectral efficiency. As traditional full-connected neural networks have been demonstrated to be powerful for equalization, their training blindness and the great complexity restrain the practical implementation. Due to the addition of prior knowledge and the simplified network structure, the FLANN has been verified as an efficient equalizer that has the impressive improvement on complexity and the similar equalization performance in many research works[20,21]. It was utilized as a post-equalizer in VLC systems for the first time in 2019. In this section, we briefly introduce the structure and principle of the FLANN for the VLC[22].

- Step 1: data pre-processing. The received signal from OSC is usually serial symbols suffering from linear and nonlinear distortions. Let us consider a one-dimensional received

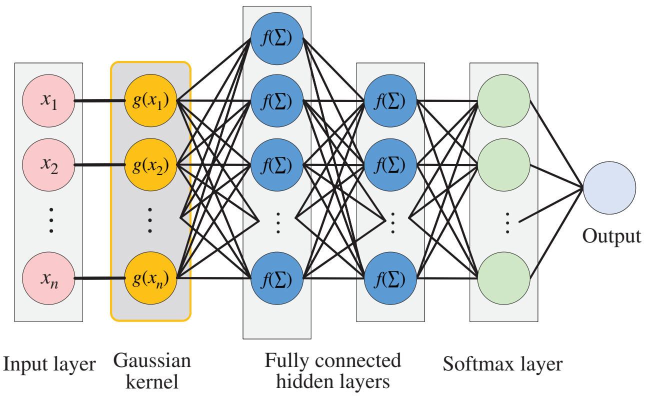

Figure 4 The structure of GK-DNN

signal $\boldsymbol{X} = [x_1, x_2, \cdots, x_m, x_{m+1}, \cdots, x_n]$ and the corresponding labels $\hat{\boldsymbol{Y}} = [\hat{y}_1, \hat{y}_2, \cdots, \hat{y}_m, \hat{y}_{m+1}, \cdots, \hat{y}_n]$. As illustrated in Fig. 3(a), the long received-signal is converted to several short sample symbols by a sliding window with a certain length m (the value of m must be odd) and the sliding step length of 1. The first column of the sample symbols (from right to left) is $[x_1, x_2, \cdots, x_m]$, and the ith column is $[x_i, x_{i+1}, \cdots, x_{i+m-1}]$. The corresponding label for every column of the sample symbols is the $\hat{y}_{i+\frac{m-1}{2}}$ for the $[x_i, x_{i+1}, \cdots, x_{i+m-1}]$. The objection of this pre-processing operation is to equalize one received symbol considering the contribution of its adjacent symbols.

- Step 2: FLANN equalization. The input sample symbols are expanded by function link layer using one certain $f(\cdot)$. For example, if the r-order polynomials expansion is utilized, the output pattern of function link layer for $[x_i, x_{i+1}, \cdots, x_{i+m-1}]$ is $\boldsymbol{S} = [x_i, x_i^2, \cdots, x_i^r, x_{i+1}, x_{i+1}^2, x_{i+1}^r, \cdots, x_{i+m-1}, x_{i+m-1}^2, \cdots, x_{i+m-1}^r]$ to add the consideration of high-order nonlinearity for ANNs. Similarly, the function can also be Gaussian, Fourier basis functions and other trigonometric polynomials (e.g. Legendre, Chebyshev, etc). Then the output pattern of function link layer is connected to the output node by weights defined by $\boldsymbol{W} = [w_1, w_2, \cdots, w_k]^{\mathrm{T}}$. The k is the length of output pattern. Therefore, for the input $[x_i, x_{i+1}, \cdots, x_{i+m-1}]$, the corresponding output is given by $y_{i+\frac{m-1}{2}} = \boldsymbol{W}\boldsymbol{s}$, thus the equalized signal $\boldsymbol{Y}$ is given by concatenating all the outputs with the serial of inputs. The FLANN is trained by the back-propagation algorithm to minimax the mean square error between predicted received signals and transmitted signals.

B. Gaussian Kernel Aided Post-Equalization Algorithm

The DNN based post-equalization and decision algorithm can effectively reduce the influence of nonlinear distortion on the performance of underwater visible light communication (UVLC) systems. However, due to the slow convergence rate of the DNN training process, the post-equalization and decision algorithm based on DNN is difficult to apply to actual UVLC systems. To accelerate the DNN training process, Ref. [10] pre-converged the input feature values of the DNN through Gaussian kernels, and proposed a Gaussian kernel aided post-equalization algorithm to reduce the training time by 47%. Consequently, under a 1.2 m underwater wireless transmission, the PAM8 modulated UVLC system achieved 1.5 Gbit/s underwater high-speed optical wireless communication for the first time. The application potential of DNN algorithm in underwater optical communication field is proved. Fig. 4 provided the structure of GK-DNN. The expression of the Gaussian kernel is

$$k(t,t')_i = \mathrm{e}^{-(\frac{\pi(t-t')}{a})^2} = \mathrm{e}^{-(\frac{\pi((i)-(i+1)/2)}{a})^2} = \mathrm{e}^{-(\frac{\pi(i-1)}{2a})^2}, \quad i = 1, 2, \cdots, n_{f-1}, n_f, \tag{1}$$

$$a = \frac{1}{\beta}\sqrt{\frac{\log 2}{2}}, \tag{2}$$

where a is a parameter that controls the scope of the Gaussian kernel, which is related to 3 dB bandwidth $1/\beta$. The process of GK-DNN based signal equalization and decision is described in Algorithm 1.

Algorithm 1 Algorithmic description of GK-DNN

Input:
Feature sets: $\boldsymbol{x}_m = [I_{1+m}, I_{2+m}, \cdots, I_{n_f-1+m}, I_{n_f+m}]$,
Amplitude coefficient vector: $\boldsymbol{k} = [k_1, k_2, \cdots, k_{n_f-1}, k_{n_f}]$,
The number of feature sets: M,
Weights of the GK-DNN at the lth hidden layer: $\boldsymbol{W}^l$,
Bias of the GK-DNN at the lth hidden layer: $\boldsymbol{b}^l$.
Output:
The predicted signal $\boldsymbol{l} = [I_1, I_2, \cdots, I_{M-1}, I_M]$.

```
L = [−7, −5, −3, −1, 1, 3, 5, 7]
for m = 0 to M − 1 do
    g(x) = x_m ∘ k = [I_{1+m}k_1, I_{2+m}k_2, ··· , x_{n_f−1+m}k_{n_f−1}, x_{n_f+m}k_{n_f}]
    O = W^3 ReLU(W^2 ReLU(W^1 g(x) + b^1) + b^2) + b^3
    for j = 0 to 7 do
        P(y = L_j | x_m)_j = e^{O_j} / Σ_{i=1}^{n} e^{O_i}
    end for
    l_m = arg max(P)
end for
return Predicted signal l
```

C. Dual-Branch Multi-Layer Perception Post-Equalization Algorithm

Although GK-DNN can effectively compensate the nonlinear distortion in UVLC systems and accurately judge the PAM signal, its high space complexity occupies extensive computing resources. To solve the problem that the deep neural network post-equalization algorithm has high complexity and is difficult to be applied in actual UVLC systems, Ref. [23] reconstructed the structure of multilayer perceptron (MLP) post-equalization algorithm based on the structure of Volterra se-

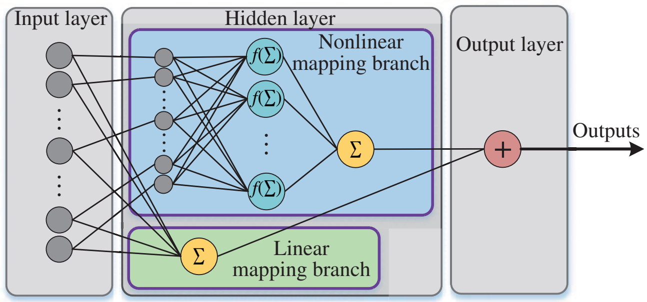

Figure 5 The structure of DBMLP

Algorithm 2 Algorithmic description of DBMLP

Input:

Feature sets: $\boldsymbol{x}_m = [I_{1+m}, I_{2+m}, \cdots, I_{n_f-1+m}, I_{n_f+m}]$,

The number of feature sets: M,

Weights of the DBMLP at the lth hidden layer: $\boldsymbol{W}^l$,

Bias of the DBMLP at the lth hidden layer: $\boldsymbol{b}^l$.

Output:

The predicted signal $\boldsymbol{l} = [l_1, l_2, \cdots, l_{M-1}, l_M]$.

for $m = 0$ to $M-1$ **do**
  $y_1 = \boldsymbol{W}^1\boldsymbol{x} + \boldsymbol{b}^1$
  $y_2 = \boldsymbol{W}^{2,2}\tanh(\boldsymbol{W}^{2,1}\mathrm{hw}(\boldsymbol{x}_m) + \boldsymbol{b}^{2,1}) + \boldsymbol{b}^{2,2}$
  $l_m = y_1 + y_2$
end for
return Predicted signal $\boldsymbol{l}$

ries post-equalization algorithm as a template, and proposed a dual-branch MLP post-equalization algorithm, which is provided in Fig. 5. DBMLP combines the advantages of linear adaptive filters and MLP, which could reduce the algorithm complexity by 74.1% and improves the algorithm's bit error rate (BER) performance. Consequently, 3.2 Gbit/s high-speed underwater communication has been realized in UVLC systems based on carrierless amplitude and phase (CAP) 64 modulation, which could be the highest rate of UVLC systems based on single-chip LED in the world at that time. The process of DBMMLP based signal equalization is described in Algorithm 2. The hollow layer could be expressed as

$$\begin{aligned}&\mathrm{hw}\left(\left[x_{n-\frac{L-1}{2}}, x_{n-\frac{L-1}{2}+1}, \cdots,\right.\right.\\ &\left.\left.x_{n-1}, x_n, x_{n+1}, x_{n+\frac{L-1}{2}-1}, x_{n-\frac{L-1}{2}}\right]\right) = \\ &\left[x_{n-\frac{L-1}{2}}, x_{n-\frac{L-1}{2}+1}, \cdots, x_{n-1}, x_{n+1}, x_{n+\frac{L-1}{2}-1}, x_{n-\frac{L-1}{2}}\right]. \quad (3)\end{aligned}$$

D. Frequency Slicing Deep Neural Network (FSDNN)

Another variation of DNN based equalizer is FSDNN for the application with low complexity toleration. It can be used in high-speed VLC systems based on CAP modulation. In addition, it has been demonstrated that it has the ability to decrease computation complexity of the traditional MLP[24]. The specific principle for FSDNN is briefly introduced as follows.

For the CAP transmitter, the frequency spectrum is shown in Fig. 6, which will suffer frequency fading issue after going through the VLC channel. If an MLP is intended to equalize such a received signal and try to mitigate the frequency fading issue, lots of layers and nodes are needed due to several amplitude attenuation in high-frequency domain. However, such a complex MLP structure is unnecessary for low-frequency domain with low amplitude attenuation. In this regard, the frequency spectrum of the received signal is split into two sub-bands using two root-raised cosine filters. Two sub-bands signals are respectively fed into two MLPs that have been trained individually. Once the MLPs are finished training and their weights are fixed, the sum of output signal from two MLPs is the equalized and recovered signal. It is clearly observed that frequency fading issue is successfully solved. Meanwhile, the total computation complexity of FSDNN is verified to be lower than that of one MLP when the similar equalization performance is achieved in Ref. [24].

E. Joint Time-Frequency Post-Equalizer Deep Neural Network

All the networks introduced in the previous sections are based on the time-domain signal only. However, in the experiments, it is non-negligible that the spectrum of those signals processed by time-domain neural networks has a noticeable difference with the spectrum of the original signals, which means the signal in time domain itself does not contain full information for the learning of the neural network. Therefore, more information should be provided to the network directly for a better performance in the distortion compensation.

The TFDNet[25], inspired by the image processing process, takes both the data in time domain and frequency domain, and therefore has an enhanced performance. The short time Fourier transformation (STFT) is used in TFDNet to combine the information in the two domains. The STFT matrix is denoted by

$$\boldsymbol{Y} = \mathrm{STFT}(y(n)), \quad (4)$$

where $y(n) \in \mathbb{R}$ denotes the received signal in time domain with a total length of N. Each row of the STFT matrix $\boldsymbol{Y}$ is a vector of a certain frequency f, defined as

$$\boldsymbol{Y}(f) = [\boldsymbol{Y}_1(f), \boldsymbol{Y}_2(f), \cdots, \boldsymbol{Y}_C(f)], \quad (5)$$

and the kth element of $\boldsymbol{Y}(f)$ is

$$\boldsymbol{Y}_k(f) = \sum_{n=-\infty}^{\infty} y(n)g(n-kR)\mathrm{e}^{-\mathrm{j}2\pi fn}, \quad (6)$$

where $g(n)$ denotes the selected window function with length M avoiding the spectral ringing, and $R = M - L$ denotes

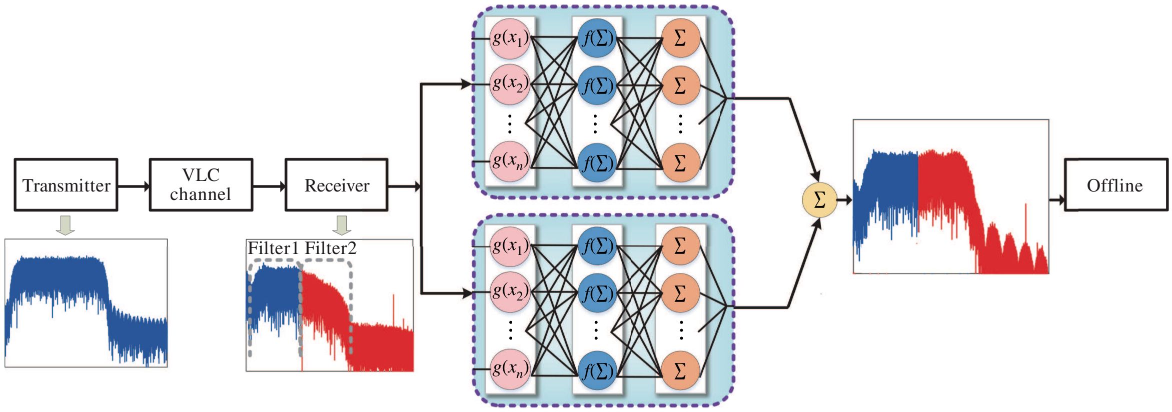

Figure 6 The schematic of frequency slicing DNN[24]

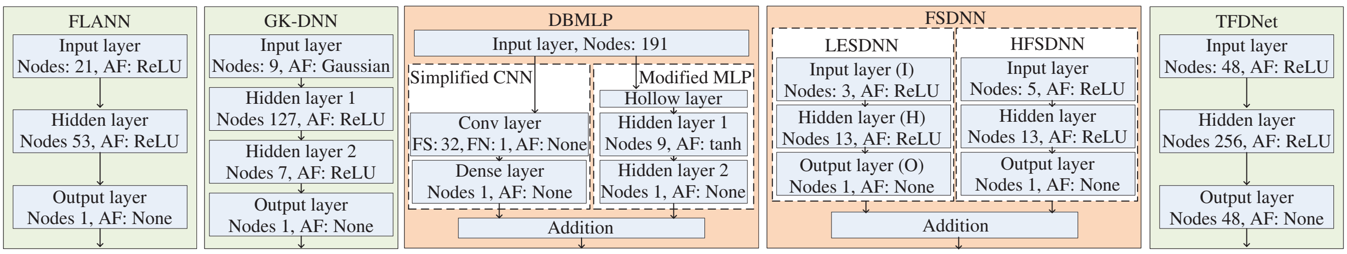

Figure 7 The structures of FLANN, GK-DNN, DBMLP, FSDNN and TFDnet

Algorithm 3 Algorithmic description of TFDNet

Input:

Received signal: $y(n)$,

Select window function: $g(n)$,

The trained network: $\boldsymbol{L}$,

The network parameters: $\boldsymbol{\Theta}$.

Output:

The reconstruct signal $\hat{x}(n)$.

1: $\boldsymbol{Y} = \mathrm{STFT}(y(n), g(n))$

2: $\hat{\boldsymbol{Y}} = \boldsymbol{L}(\boldsymbol{Y}, \boldsymbol{\Theta})$

3: $\hat{x}(n) = \mathrm{ISTFT}(\hat{\boldsymbol{Y}})$

4: **return** Reconstructed signal $\hat{x}(n)$

stride between each adjacent pair of discrete Fourier transform (DFT) in the STFT, with M denoting the window length and L denoting the overlap at the window edges.

The STFT matrix $\boldsymbol{Y}$ is similar to an image with the size of $2D \times \left\lfloor \frac{N-L}{M-L} \right\rfloor$, where D is the DFT points. The network takes the columns in $\boldsymbol{Y}$ one by one. And finally, the reconstruct signal $\hat{x}(n)$ is obtained by the inverse STFT (ISTFT) as

$$\hat{x}(n) = \int_{-\frac{1}{2}}^{\frac{1}{2}} \sum_{k=-\infty}^{\infty} \hat{Y}_k(f) \mathrm{e}^{\mathrm{j}2\pi f n} \mathrm{d}f = \sum_{k=-\infty}^{\infty} \hat{x}_k(n). \tag{7}$$

The working procedure of the TFDNet can be described as Algorithm 3.

IV. Discussion

Fig. 7 shows the detailed structures of the introduced five networks: FLANN, GK-DNN, DBMLP, FSDNN and TFDNet. Noticing that the data pre-processing parts of FLANN and TFDNet are not illustrated, the network structures of these two networks are the most simple ones.

Inspired by the understanding of VLC systems, each network shows a novel optimizing perspective. The design of FLANN is to enhance the functionality of the simple ANN. With ANN itself, the equalizing performance is poor for that the network is too brief. FLANN introduces the data pre-processing layer with the prior knowledge of VLC systems, and thus improve the ANN accuracy.

GK-DNN is proposed to reduce the training iteration number, which is driven by the practical analysis in the experiments. It shows that though the inter-symbol interference (ISI) exists between the symbols, the larger the distance between two symbols is, the less the ISI will be. Thus, a Gaussian kernel function is applied to the input data, and reduces the number of training iterations by 47% with the similar performance.

The system transfer function model can be divided into the linear part and the nonlinear part. However, neural networks are more likely to learn the nonlinear part, causing that the linear part is treated as nonlinear part as well. DBMLP

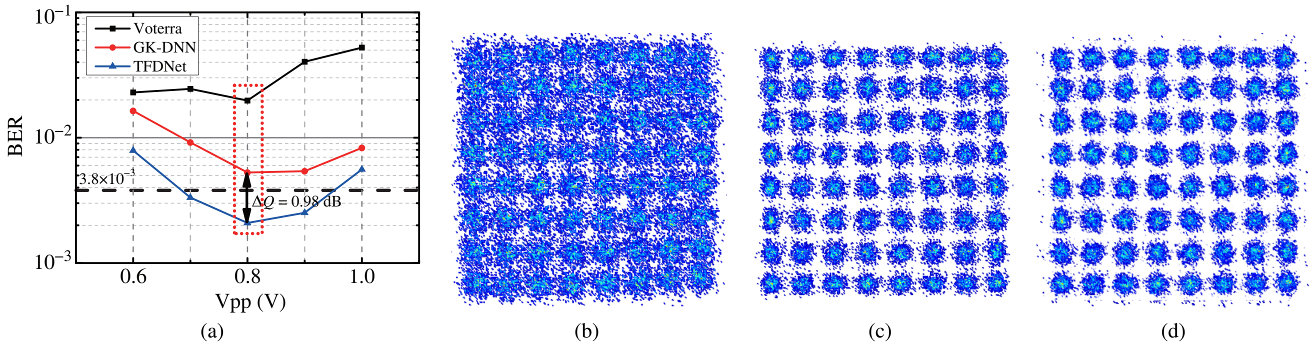

Figure 8 An experiment comparing the actual performance of Volterra, GK-DNN and TFDNet equalizers[25]: (a) BER versus Vpp at a data rate of 2.85 Gbit/s; (b) Volterra at 0.8 V; (c) GK-DNN at 0.8 V; (d) TFDNet at 0.8 V

processes the data with two sub-networks in parallel. One of the sub-networks, which is a convolutional neural network (CNN) without activation functions, takes only the linear portion, while the other one, which is an MLP with activation functions, takes the nonlinear portion.

FSDNN pays attention to the frequency domain. In a VLC channel, the low frequency part of the signal is well transferred, but the high frequency part is dramatically attenuated with the frequency going up. Therefore, it is not reasonable to use a same network to learn both the low frequency part and the high frequency part. With two sub-networks learning each part of the signal, FSDNN has a good performance among the entire frequency domain.

TFDNet, as introduced in section III.E., takes both time-domain information and frequency-domain information. With the help of Fig. 7, it is clear that the structure of TFDNet is not complex compared with the other networks listed. Furthermore, Fig. 8 shows an experimental comparison among the classical methods of Volterra equalizer, GK-DNN and TFDNet when the data rate is 2.85 Gbit/s. ML based methods have a significant improvement in the BER performance, and TFDNet shows the best performance with a 0.98 dB improvement in Q factor at the point with the signal's peak-to-peak voltage being 0.8 V.

It is clear that ML technologies have greatly enhanced the performance of VLC systems in terms of nonlinear mitigation. The universal approximation theorem describes that a neural network has the capability of fitting any complex nonlinear functions with proper parameters and structures. Furthermore, the VLC system model has not been established due to the complex nonlinear effect. Therefore, neural networks could be a solution to these challenges. However, neural networks need a lot of training data with enough randomness in order to avoid the over-fitting, as well as the computing power for both training and testing. Particularly, in the practical deployment, the communication terminals might have limited computing ability. The design of the network is critical for the network, determining whether it can be easily deployed.

V. Conclusion

In this paper, five latest ML applications in VLC are introduced, including FLANN, GK-DNN, DBMLP, FSDNN and TFDNet. By the time, TFDNet is the ML application in VLC with the best performance. GK-DNN and FLANN have the simplest structure with a moderate performance for the compact systems with less computing power. DBMLP and FSDNN show novel ideas about slicing the network into two parts for different features based on the understanding of VLC systems. As a newly developed subject, neural network has shown its power in fitting arbitrary combination of linear or nonlinear transfer function models. Compared with other research fields like image processing, the application of ML in VLC has just reached the initial stage by now. It is convincing that with the further research on ML in VLC, it will show its extraordinary talents, and thus carry forward the performance of VLC systems.

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