MPT-Transformer based post equalizer utilized in underwater visible light communication system

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***Abstract*—In this work, we proposed a mixed precision training-based transformer (MPT-Transformer) model to process signal post-equalization in underwater visible light communication channel (UVLC). The application of MPT-transformer model in 1.2m underwater experimental platform using 64 quadrature amplitude modulation-carrierless amplitude (64QAM-CAP) modulation achieves 3.08Gbps while the bit error rate (BER) below the 7% forward error correction (FEC) limit of 3.8×10^{-3}, which is 120Mbps faster than traditional least mean squires (LMS) method.**

Keywords — underwater visible light communication, transformer model, signal post-equalization

I. INTRODUCTION

Visible light communication (VLC) technology is a long-standing hot topic in underwater optical wireless communication (UWOC) [1, 2]. UWOC systems suffer from severe absorption and scattering because of complex underwater environment. Plus, nonlinear amplification in driving circuit and receiver will also lead to high distortion of visible light signal [3]. Therefore, investigating advanced signal post-equilibrium methods to compensate for signal's transmission damage is of great significance. The rapid development of neural network (NN) technology provides infinite possibilities for post-equalization of UVLC [4, 5]. Zhao et al. presented a Gaussian-kernel aided deep neural network (DNN) algorithm which effectively compensate the non-linear attenuation in UVLC [6] and proposed dual branch DNN based post equalizer which achieved the fastest bitrate of single LED in UVLC system [7]. Chen et al. put forward a time-frequency joint DNN in signal post-equalization [8]. Recently, an attention mechanism based transformer model is proved to be an outstanding method to process natural language signal [9, 10] which may have potential advantage in signal post-equalization.

In this work, we proposed a MPT-Transformer model to compensate signal nonlinear damage. The maximum bitrate achieved 3.08Gbps with the 7% FEC limit over 1.2m underwater channel using 64QAM-CAP, which improves 120Mbps compared to traditional LMS post equalizer.

II. PRINCIPLE

At the receiver end, there exists inter-symbol interference (ISI) resulting coupling correlation among waveform data. In order to more comprehensively extract time dimension features of waveform data, time sliding window technology is used for preprocessing. In detail, the time window length is 45 and the time step is 1. Finally, the dataset is formed whose attributes are time sliding waveform data in receiver end, while label is the original data in transmitter end. It is worth noting that target data corresponds to attribute centric data. However, our goal is to use the optimal model to fit time sliding window data as closely as possible to the target. In experiments, 60% dataset is used as training set, while 40% as validation set and test set.

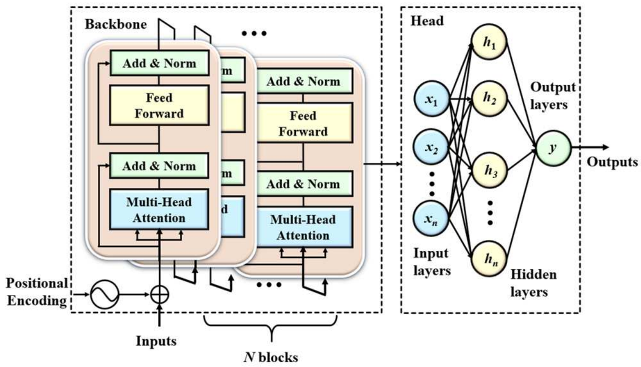

Fig.1 Frame structure of the MPT-Transformer.

Transformer is a deep learning model that has achieved great success in natural language processing [9]. Because it can capture long-term dependencies and interactive relationships, Transformer is also widely used in time series prediction. In this experiment, waveform-level data balancing can be regarded as a time series autoregressive problem. We propose the MPT-Transformer, as shown in Fig. 1. During training, we first use multiple encoders as the feature extractor and fully connected layer as the regression fitter. In MPT-Transformer, the input is time sliding window data and the output is fitted waveform data. In this task, there are four modules in Encoder: position encoding, multi-head attention mechanism, residual connection, layer normalization and feed forward [9]. There are three encoder blocks constitutes a deep feature extractor and two fully connected layer used for fitting regression with ReLU activation function. To prevent overfitting, Dropout regularization was added between hidden layer and linear output layer.

Computational complexity of Transformer is extremely high. Under the condition of limited computing resources, we adopt the mixed precision training strategy, which uses both 16-bit and 32-bit floating-point types in the model to speed up operation and reduce memory usage [10]. Importantly, half-precision floating-point numbers store network weights and gradients. Since the numerical representation range is squeezed during training, gradient underflow can be occur. In this case, model parameters cannot be updated and never converge. To solve such a problem, we use loss scaling optimization. It enlarges the loss value appropriately when calculating loss and reduces gradient by the same multiple when optimizer updates parameters to avoid gradient underflow [10].

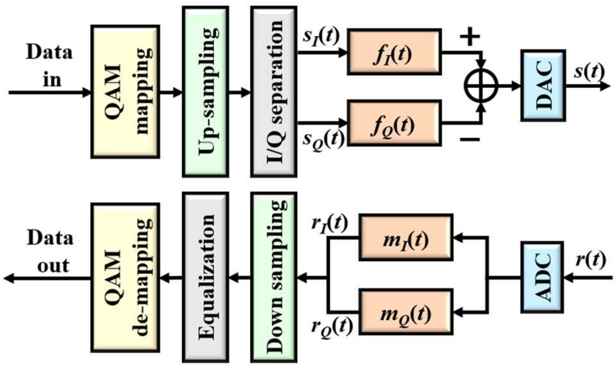

Fig.2 Principle of the single carrier CAP modulation and demodulation.

According to the previous research, CAP modulation has the advantages of low complexity and high spectral efficiency. Comparing with the quadrature amplitude modulation (QAM), which is done in the analog domain and transmit complex signal, CAP modulation is done in the digital domain and modulate the real signal.

Fig. 2 is the principle of CAP modulation and de-modulation [11]. Firstly, we generate the original bit sequence and map it into complex 64QAM symbols. After up-sampling, the signal is separated into the in-phase and quadrature components $s_I(t)$ and $s_Q(t)$. Then, we use two orthogonal matched filters $f_I(t)$ and $f_Q(t)$ which can be expressed as (1) for pulse shaping.

$$\begin{cases} f_I(t) = g(t)\cos(2\pi f_c t) \\ f_Q(t) = g(t)\sin(2\pi f_c t) \end{cases} \quad (1)$$

Here, $g(t)$ is the square root raised-cosine filter and f_c represents the center frequency of the CAP signal. After adding the two orthogonal signals, the 64QAM-CAP signal is obtained for digital-to-analog conversion. Finally, the generated signal $s(t)$ for transmission can be expressed as:

$$s(t) = s_I(t) \otimes f_I(t) + s_Q(t) \otimes f_Q(t) \quad (2)$$

where $\otimes$ represents the convolution operation.

At the receiver, the signal is sampled and quantified with an analog-to-digital convertor (ADC) and separated into the in-phase and quadrature components for matched filtering:

$$\begin{cases} r_I(t) = r(t) \otimes m_I(t) \\ r_Q(t) = r(t) \otimes m_Q(t) \end{cases} \quad (3)$$

where the matched filter can be obtained through $f_I(t)$ and $f_Q(t)$:

$$\begin{cases} m_I(t) = f_I(-t) \\ m_Q(t) = f_Q(-t) \end{cases} \quad (4)$$

After combining $r_I(t)$ and $r_Q(t)$, we finally get the complex signal for down-sampling, equalization and QAM de-mapping.

III. EXPERIMENTAL SETUP

Fig. 3 shows the experimental setup of the proposed scheme.

At the transmitter side, we first generate the original bit sequence and map it into 64QAM signal. After up-sampling, the 64QAM signal is separated into the in-phase and quadrature components. After CAP modulation, the real time domain signal is fed into an arbitrary waveform generator (AWG) for transmission. The transmitted signal is firstly amplified by an electrical amplifier (EA). Then the amplified signal is coupled with the direct current (DC) with a bias-Tee and a blue LED (450nm) is driven. After a 1.2-meter water tank, the beam is focused on a commercial PIN through a lens for optical-to-electrical conversion. After an EA, the received signal is sampled by an oscilloscope (OSC) and sent to a personal computer for off-line digital signal processing.

The proposed MPT-Transformer algorithm is used for signal equalization. By two matched filters, the signal is then separated into the in-phase and quadrature components. After down-sampling, the signal is fed to a least mean squares (LMS) equalizer and finally de-mapped into 64QAM symbols for BER testing.

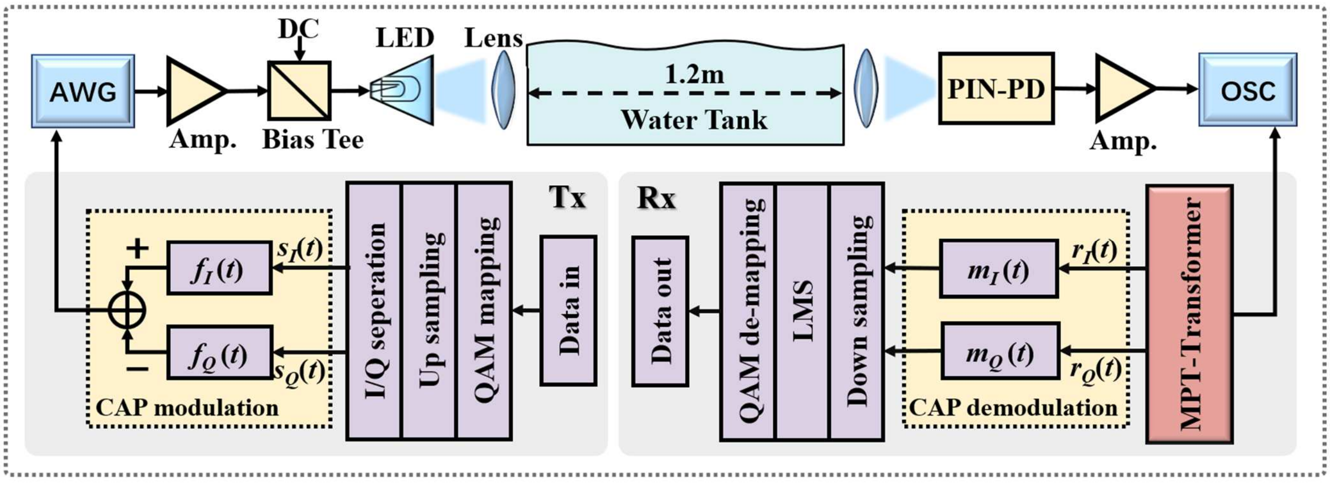

Fig.3 Experimental setup of the underwater visible light communication system.

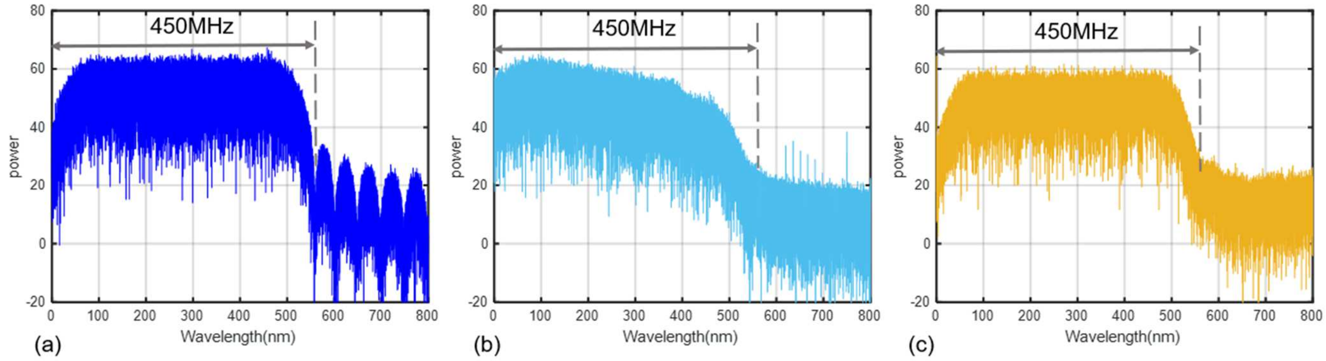

Fig.4 The FFT spectra for (a) the original signal, (b) the received signal, (c) recover signal after MPT-Transformer.

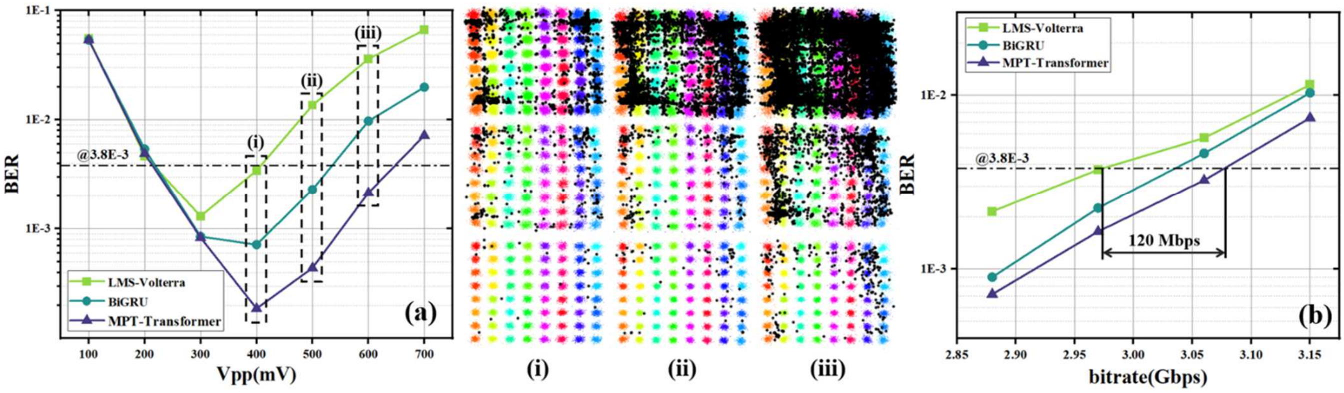

Fig.5 (a) Measured BER as a function of the input Vpp, (b) Measured BER as a function of the data rate.

IV. Results and Discussion

Fig.4 demonstrates the frequency spectrums of original signal, received signal and recover signal after MPT-transformer post-equalizer respectively. Compared Figure4(a) and Figure4(b), the received signal is attenuated at high frequency while more noise is generated at low frequency after transmission in underwater channel. After post-equalization, the recovered signal spectrum can fit the original signal effectively, the MPT-transformer post-equalizer compensates the high frequency attenuation and eliminates low frequency noise.

As we know the nonlinear effect will become severe when increasing the driving voltage of the silicon LED. In order to make a comparison of different post-equalization method, we measured the BER as a function of the input Vpp, as shown in Fig.5(a). Clearly, we can see an optimized operation range of Vpp can be found around 400mV. If the input voltage is lower than 400mV, the signal will be deteriorated by the system noise. The relatively lower SNR will become a detrimental effect of the system. When the input voltage is around 100mV, the post equalization will be insufficient to achieve the threshold of hard FEC of 3.8E-3. On the other hand, if the input voltage is increased larger than 400mV, the system will be suffered for nonlinear effect. The proposed MPT-Transformer scheme is evidently the best post-equalizer compared with traditional LMS-Volterra scheme and BIGRU scheme. The best BER is around 1.87E-4, meanwhile the LMS-Volterra can achieve merely 3.4E-3. If the input vorlage is adjusted to be larger than 700mV, then all kinds of post-equalizers will become invalid, and the measured BER will soon be larger than FEC threshold.

As the experimental results shown in Fig. 5(b), we compared the change of BER as the Bitrate increases from 2.85Gbps to 3.15Gbps using 3 different post-equalizer. Looking at the horizontal direction, the BER under all of three post-equalizer increases as the bit rate enlarges because the error of every single bit will diffuse in high bitrate. Meanwhile, we can figure out that MPT-Transformer model occupies the fast bitrate which is 3.08Gbps as the BER is under the 7% FEC limit of $3.8*10^{-3}$ while the BiGRU took the second place and the LMS-Volterra is the worst one. Compared to traditional LMS-Volterra method, MPT-Transformer achieves 120Mbps improvement.

V. Conclusion

In this paper, we propose a Transformer model based on mixed precision training for waveform-level post-equalization in UVLC. Deep multiple encoders is used for feature extraction and fully connected layers is used to fit the data. This model can capture nonlinear effects of waveform data in receiver end and approximate the transmitted waveform data as much as possible from the time-domain signal to complete post-equalization. In our experiment, at a 7% forward error correction (FEC) threshold, we achieved a rate improvement of over 100Mbps compared to traditional signal processing methods and BiGRU methods. MPT-Transformer provides a promising solution that significantly reduces the system's bit error rate and improves the performance of communication systems.

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