Unsupervised Learning for Neural Network-Based Blind Equalization

Tao Liao, Lei Xue, Weisheng Hu, *Member, IEEE*, and Lilin Yi, *Member, IEEE*

***Abstract*— For the first time, an unsupervised learning training method was proposed for neural network (NN)-based blind equalization in intensity modulation and direct detection (IMDD) system. The whole scheme can directly train an NN-based equalizer with only the received signal rather than original symbols as reference. Besides, the unsupervised learning can also help a well-trained NN to keep its performance in face of varying system status, such as wavelength shift and bias fluctuation, in practical applications. We evaluate the performance of the proposed scheme in a 50 Gb/s IMDD system. The experimental results confirm that the proposed unsupervised learning can train fully-connected NN-based equalizer as well as convolutional neural network (CNN)-based equalizer to reach the same performance as the one trained by supervised learning. Besides, in face of signals with different bias current of the directly-modulated laser (DML), the unsupervised learning method can train the NN to keep the best performance. It can be proved that the scheme can help maintain the performance of NN-based equalizer against the continuous system parameter variations.**

***Index Terms*— Intensity modulation and direct detection (IMDD), equalization, neural network (NN), unsupervised learning.**

I. Introduction

Machine learning, especially neural network (NN) has shown its power on modelling, classification and prediction, which has been widely used for computer vision and speech recognition. Recently NN has also been used as an efficient tool in optical communications to compensate the transmission impairments, including both linear and nonlinear distortions. In high-speed intensity modulation and direct detection (IMDD) systems, the linear distortions include fiber dispersion and bandwidth-limitation effect, while the nonlinear distortions mainly come from the transmitter and receiver's nonlinearities. It is proved that an NN can fit and express any functions if it has enough nodes with more than one hidden layer [1]. Therefore, equalizer based on NN and some variants of NN can theoretically mitigate all the resolvable distortions. Fully-connected NN is the simplest and most widely-used one, which is employed in many works as an equalizer and shows better performance than some conventional algorithms [2]–[8]. To achieve higher performance, some variants of NN such as convolutional neural network (CNN) and recurrent neural network (RNN) are leveraged in equalization [9]–[12].

All these works shows the capability of NN and its variants in equalization. However, in practical applications, the main issue of the NN-based equalizer is that a well-trained NN with fixed parameters cannot adapt to the system status variations, such as wavelength shifting induced by temperature change, bias fluctuation and component aging. Multi-task training [13], which considers some possible input conditions, may solve the problem to some extent. This strategy should train the NN model with data of different system parameters. Though it works for signals under different conditions, the cost is that the model accuracy is degraded. Therefore, an adaptive NN-based equalizer is required to guarantee the best equalization performance under varying input conditions.

In this work, for the first time, we propose an unsupervised learning scheme for NN-based equalizer in IMDD system and evaluate its performance in a 50 Gb/s passive optical network (PON) system. The experimental results confirm that the unsupervised learning method can train a fully-connected NN-based equalizer and CNN-based equalizer to reach the same performance as the model trained by the traditional supervised learning method. Furthermore, the unsupervised learning method can also help maintain the performance of a well-trained NN-based equalizer with only the received signal when the status of transmission system is shifting.

II. Principle

For a classification model of NN-based equalizer, the input is the sampled sequence of signal and the output is a vector activated by *Softmax*, corresponding to the category of symbols. For a 4-pulse amplitude modulation (PAM4) signal, the express of *Softmax* is

$$y_i = Softmax(x_i) = \frac{e^{x_i}}{\sum_{j=1}^{4} e^{x_j}}, \tag{1}$$

and the output vector is

$$y = \{y_1, y_2, y_3, y_4\}, \tag{2}$$

where y_i denotes the output weight of ith level for PAM4. The sum of the vector y is 1 and the max value y_i in y means the decision of the equalized sample is ith symbol. Based on this type of NN-based equalizer, our proposed unsupervised learning scheme is illustrated in Fig. 1(a).

The received signals will be first resampled to one sample per symbol. Then, a **Rough Decision Policy** is used to initialize the new labels for the signal samples. This Rough

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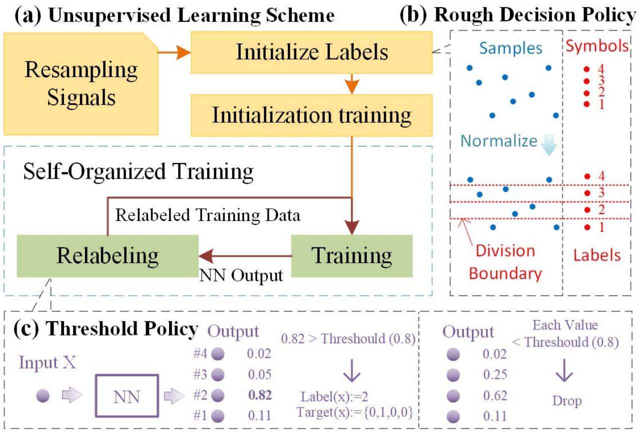

Fig. 1. Scheme of unsupervised learning for NN-based blind equalizer. (a) Scheme flow, (b) Rough Decision Policy for initializing labels, (c) Threshold Policy for relabeling.

Decision Policy can be hard decision, or some simple blind equalization and decision methods, e.g. k-mean. A simple hard decision method leveraged in this work is shown in Fig. 1(b). For PAM4, the label vector is $\{1, 2, 3, 4\}$, which will be normalized to $\{-1.342, -0.447, 0.447, 1.342\}$, so the division boundary should be $\{-0.894, 0, 0.894\}$. The referred boundary will be applied to divide the normalized samples of the received signal, then the samples will be labeled according to the partition.

The samples with the new labels can be constructed as the initialization training data for NN. Note that a high decision accuracy is not necessary since the initialized labels are used to drive the first training to an approximate destination. With the initialized labels, an initialization training will be conducted as a supervised learning. This training procedure will be executed in only several iterations to prevent the NN from completely fitting the inaccurate data.

Finally, a self-organized training iteration will be launched to train the model. This process consists of two steps, relabeling and training. Relabeling updates the labels based on the output of current model to obtain more accurate training data which will help to improve the actual training accuracy. We design a **Threshold Policy** for relabeling as shown in Fig. 1(c). Since each value in the output vector of classifier model denotes the classified probability of its corresponding class. The Threshold policy relabels the data based on these probabilities. Specifically, the threshold is set to thr, if the max value in the output vector is greater than thr, then the corresponding class will be set as the new label for the input data, otherwise the data will be dropped out. As the example in Fig. 1(c), the thr is 0.8, and the output vector is $\{0.11, 0.82, 0.05, 0.02\}$. Since the weight of second level is greater than thr, the label of this input data will be set as the second symbol, where the training target should be $\{0, 1, 0, 0\}$. For $\{0.11, 0.62, 0.25, 0.02\}$, no weight is greater than thr, hence this data will not be chosen in training.

With the new labels and target vectors, the selected data can drive a new turn of training. The training step will last only one or several epochs, as it should not overfit the partially correct data. These two steps will run in turn repeatedly.

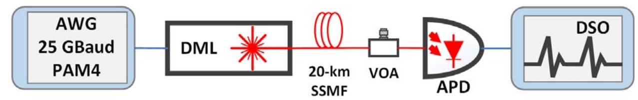

Fig. 2. Experimental setup of 25 Gbaud/s PAM-4 IMDD PON system based on 10G-class DML.

Different from supervised learning, unsupervised learning has no reference data to measure the accuracy, so it cannot directly verify its training convergence based on accuracy performance. Therefore, we define a new judgement of convergence of such scheme, which is that the decisions of training signal have no evident change in several iterations.

Besides, it also lacks a direct way to check the correctness of the training result without the reference data. To address the problem, we provide a statistic-based method to check the effectiveness. As the training sequence is a random sequence, the symbols should follow the uniform distribution. However, once the NN model overfits the partially correct training data, the NN will get an error convergence. The output symbols of training sequence from such invalid NN model will have an unbalanced distribution. Therefore, the method justifies the training result based on the distribution of output symbols. In detail, a decision sequence with the length of l is equalized by the trained NN model. The category number of the symbol is m. Let $\mathrm{d} = l/m$, we define an evaluation index called unbalanced degree as:

$$ub = \frac{\sum_{i=1}^{m} |c_i - d|}{2(l - d)}, \tag{3}$$

where c_i denotes the number of i-th symbol in such decision sequence. Obviously, $ub \in [0, 1]$. A correct model should has a small ub. It needs a proper threshold to check whether the model is correct or not, which will be discussed later.

III. Experiments and Discussion

The experimental setup is shown in Fig. 2. A Keysight M8195A arbitrary waveform generator (AWG) with a sampling rate of 64 GSa/s is applied to generate a 25 GBaud/s PAM4 based on Mersenne Twister random sequence from Matlab. The PAM4 signal is modulated on a 10G-class O-band DML. After 20-km standard single-mode fiber (SSMF) transmission, a variable optical attenuator (VOA) is applied for receiver sensitivity measurement. Then the optical signal is detected by a 20G-class avalanche photodiode (APD). The detected signal is finally sampled by a LeCroy digital sample oscilloscope (DSO) with 45-GHz bandwidth and 120-GSa/s sample rate. The sampled signal will be off-line processed in Matlab and Python.

First, we evaluate the performance and effectiveness of training with unsupervised learning for NN-based equalizer. The evaluated NN has 2 hidden layers and each of them has 128 hidden nodes, which are activated by *ReLU*. The input size is 51, while the output is a vector with 4 values activated by *Softmax*, corresponding to 4 levels of PAM4. The lengths of the training set and test set are both 100000. The training set is used to train the NN model, while the labels will be initialized and updated during the whole scheme. For all the training steps, the batch size is set to 1000. Meanwhile,

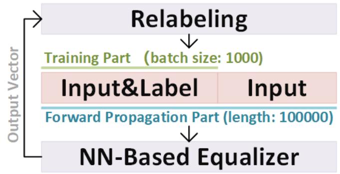

Fig. 3. Operation of self-organized training in detail.

the test set with the original symbol is applied to measure the performance of current NN model in each epoch. The received single is resampled to symbol space. The basic hard decision strategy is leveraged to initialize the labels for the training set. The initialization training is run for 3 epochs, where the whole training set with new labels will be used. After the initialization training, begin with epoch 4, the self-organized training iteration repeatedly relabels the data and trains for 1 epoch in turn, where the threshold for relabeling is set to 0.8. As shown in Fig. 3, the output vector of the whole training set will be sent to relabeling. Only part of the training set will get the label and work as the training data in new turn, but all the data will join the forward propagation to get the new output of the new trained NN model. As the accuracy increases, more and more data can get the labels and become the real training data. All of the training is run with the training optimization technique Adam [14], while the learning rate is 0.001. Each epoch, the whole test set with the original symbol will be used to measure the bit error rate (BER) performance of the current NN model after a turn of training. Besides, to verify the extendibility of this unsupervised learning scheme, we also employ it on a CNN-based equalizer. The measured CNN contains 2 one-dimensional convolution layers, where the kernel size is 5 and the kernel numbers are 6 and 15 respectively. The output of convolution layer is passed to 2 fully-connected layers with the size of 128 and 64, where the activation function is also *ReLU*. The learning rate is set to 0.0005 to avoid the gradient explosion for the first several epoch training, while a batch normalization [15] is leveraged to accelerate the training.

The BER performance of both the proposed unsupervised learning scheme and the conventional supervised learning method are compared for the NN and CNN model. The result is shown in Fig. 4. Fig. 4(a) validates that unsupervised learning can effectively train NN-based equalizer to reach the same performance as supervised learning. The first three epochs corresponding to the first three points belong to initialization training, which trains the model with the initialized labels from hard decision. Then the self-organized training iterations correct the labels and model parameters gradually and finally reach the best performance. The convergence speed of unsupervised learning is quite slower than the supervised learning. The main reason is that during the iterations, the training targets are partially correct.

Furthermore, the proposed scheme also works for CNN-based equalizer, as shown in Fig. 4(b). The result verifies the extendibility and generality of the unsupervised learning scheme. Since most models of NN and its variants follow a same upper framework, the proposed scheme should work for most common equalizer based on NN or some similar models.

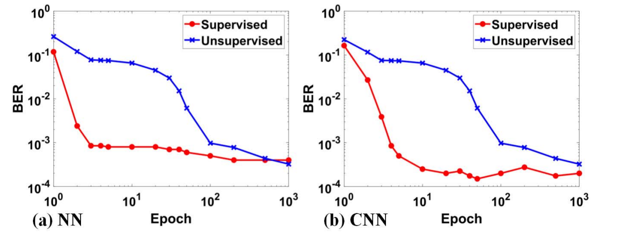

Fig. 4. BER of supervised learning and unsupervised learning versus training epoch, (a) NN, (b) CNN.

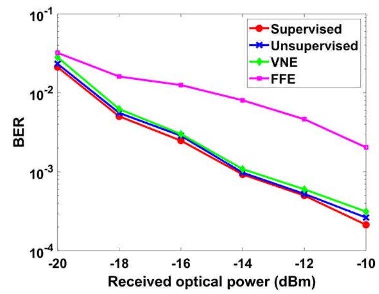

Fig. 5. BER of supervised learning and unsupervised learning versus received optical power.

Fig. 5 shows the BER of NN-based equalizer trained by supervised learning, unsupervised learning, Volterra nonlinear equalizer (VNE) and feed-forward equalizer (FFE) with the adaptive LMS algorithm over different received optical power. The VNE has three order with the size 51/11/9, while the taps of the FFE is 51. With varying qualities of the signal, the unsupervised scheme can always effectively train the NN model and reach the same performance as supervised learning. Besides, NN-based equalizer get the best performance, while VNE has a similar performance as NN, which outperform FEE.

We also check the correctness of the verification method. We set improper initialization training to lead some wrong results. Through 10 sets of test, we find that the numbers of any symbol in output sequence are approximately equal for all correct models. On the other hand, for all invalid models, the distribution of output symbols are extremely unbalanced. For an instance of the test results, to equalize a received PAM4 sequence with the length of 40000, the numbers of each symbol of a correct model are {10227, 9800, 10010, 9963}, while another invalid model gets {0, 19281, 8640, 12079}. The ub of the correct model is 0.0078, while this value of the wrong model is 0.3787. Actually, for a correct model, this value will be close to 0. Hence, a small threshold such as 0.02 is enough.

The second application of the unsupervised learning method is to maintain the performance of NN-based equalizer in face of slowly varying system status. For convenience, we select the various bias of DML in our experiment to measure this function. As we mention above, the self-organized training step can optimize a trained NN model in face of system variation, no matter which method is used to initially train the model. In this part, we use supervised learning for initial training due to its fast convergence. We initially train the NN by supervised learning and test its BER performance for different DML bias current, with or without optimization of

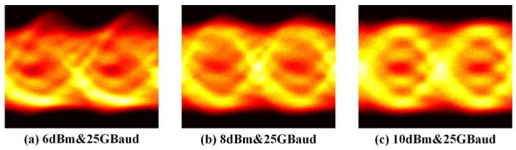

Fig. 6. Eye diagrams of 25 Gbaud/s PAM4 signals at −12 dBm receiving power with different DML bias corresponding to various output powers, which are 6, 8, 10 dBm respectively.

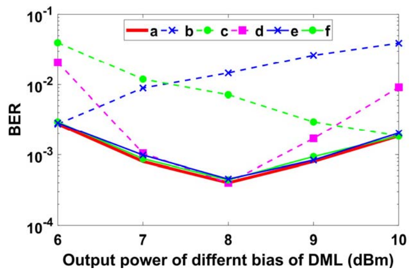

Fig. 7. BER of different data with/without optimization of unsupervised learning; (a) test after trained by supervised learning on each bias; (b), (c), (d) train with supervised learning on 6, 10, 8 dBm respectively and test on each test set without retraining; (e) initially train on 6 dBm and bias moves from 6 dBm to10 dBm with step of 1 dBm, test on each status with retraining by unsupervised learning; (f) initially train on 10 dBm, shifting opposite to (e).

self-organized training. Note that self-organized training will only optimize the model with the received signal. It updates the model based on current model parameters. The different biases of DML are related to different output power of the DML from 6 dBm to 10 dBm. For all measurements, the received power is set to be −12 dBm, while part of the received eye diagrams are shown in Fig. 6. The eye diagrams indicate that the signal behavior varies severely as the bias shifts, while also exhibiting strong nonlinearity. At each bias, 200000 symbols are captured and divided into training set and test set, while the lengths are both 100000. We measure the proposed scheme on the signal over these cases, and the experimental results are shown in Fig. 7.

As shown in Fig. 7, curve (a) shows the BER of NN trained by supervised learning on each data of different bias, which is also the benchmark to measure the performance. In curve (b), (c) and (d), the NN is trained with only one training set of a bias, respectively, while it will be tested on different data with different test set of various bias. The results indicate that the performance will continuously degrade as the deviation increases. In curve (e) and (f), the NN will be not only initially trained by supervised learning, but also optimized by unsupervised learning during the bias change from 6 dBm to 10 dBm, or from 10 dBm to 6 dBm. Here a change with step of 1 dBm is used to emulate the status shifting of the system. Each time the data is changed, the NN will be optimized to converge with the training set at the bias, then the corresponding test set is used to evaluate the BER. Compared to curve (a), (b) and (c), curve (e) and (f) verify that unsupervised learning effectively maintains NN performance against the system status changing. With Fig. 6, it is proved that the self-organized training can also adapt the various severe nonlinear behaviors.

Specifically, every time the data over one status changes to another one with different bias, NN requires about 10 epochs of self-organized training to approximately convergent. It is evidently faster than completely training a new model with the whole unsupervised learning scheme to from beginning, which requires more than 100 epochs. According to the results, the proposed scheme can help NN-based equalizer confront the slowly varying or a small jumping of the system status.

IV. Conclusion

In this work, we proposed a novel unsupervised learning scheme for NN-based blind equalizer in a 50 Gb/s IMDD system, which can be also extended to other IMDD systems with different baud rate, or even the equalizer for other optical systems. This scheme can train NN-based equalizer without original data symbols and also help a well-trained NN-based equalizer to keep its performance in face of varying system status. We experimentally confirm that the proposed scheme can train NN to get a same performance as supervised learning, while it also works for CNN, verifying its extendibility. Besides, we demonstrate its effectiveness in maintaining NN performance with the slowly shifting or a small jumping of system status, which is useful for practical applications.

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