Deep Learning Detection Method for Signal Demodulation in Short Range Multi-path Channel

Lanting Fang, Lenan Wu
School of Information Science and Engineering
Southeast University
Nanjing, China 210096
e-mail: {230139356, wuln}@seu.edu.cn

Abstract—**Signal demodulation in short range multi-path channel plays an important role in communication system. The existed wireless communication system in short range multi-channel achieve signal demodulation by using a equalizer to minimize the effect of inter-code crosstalk caused by the channel before the signal detection. However, channel equalization methods are either with high complexity or a waste of frequency resource. In this paper, we propose a deep learning based detection method for signal demodulation. The proposed method can detect the signal directly without any channel equalization methods in short range multi-path channel. The existing deep learning methods DBN and SAE can be applied to our system. Meanwhile, we propose a novel deep learning method – TTN with a lower computational complexity compared with DBN and SAE. To evaluate the performance of the proposed system, series of comprehensive simulation experiments is conducted under the environment of multi-path channels. The experimental results show that the proposed deep learning detection method can be used for signal demodulation in multi-path channel without channel equalization.**

Keywords-deep learning; multi-path channel; demodulation

I. INTRODUCTION

Signal demodulation in short range multi-channel has received considerable attention in communication system, recently. Existing demodulation methods mainly use a equalizer to equalize multi-path effects and inter-symbol interference before the signal detection. We can classify the existing equalization methods into two categories: pilot based channel estimation methods and blind channel estimation methods.

Pilot based channel equalization methods send pilot sequences to track the channel to achieve a equalization effect. Lim et al. [1] propose a novel module charge equalizer utilizing the magnetizing energy of the multiwinding transformer for the equalization among modules. Das et al. [2] apply artificial neural network trained with particle swarm optimization for the problem of channel equalization. Li et al. [3] propose a visible light communication based on a post-equalization circuit, where the post-equalization circuit contains two passive equalizers and one active equalizer. Pilot channel equalization based method has a low spectral efficiency, and it is easy to cause the interference. At the same time, the transmission of the pilot signal requires a high cost.

Blind channel equalization methods equalize transmitted signal from the received signal. In [4], a novel fast blind equalizer is obtained by using the direct calculations from a channel matched filter decision feedback equalizer. Bordin et al. [5] proposed a model in which the unknown unit-norm parameter vectors have Fisher-Bingham prior distributions. Xu et al. [6] propose two new blind learning algorithms to achieve robust convergence for linear or nonlinear equalization. Blind channel estimation does not require any training sequence, while semi-blind channel estimation requires a shorter training sequence. However, the general blind estimation and semiblind estimation methods have high computational complexity and may cause phase ambiguity, error propagation, and slow convergence.

Therefore, it is of great significance to propose a method that can demodulate the signal under the short range multi-path channel with a high spectral efficiency and a low complexity. One way to solve this problem is to use machine learning based method to learn the signal features before the communication process. Machine learning method are frequently used in signal communication. Xianqing Chen and Lenan Wu have proposed a new approach for the nonlinear demodulation based on the support vector machine [7], and the bit error rate (BER) performance can be improved significantly by using the SVM classifier. Fang et al. [8] further propose a binary signal classification method based on continuous wavelet transform and feature extraction. One of the most important factors in achieving accurate signal demodulation is that the machine learning model must be able to distinguish the differences between the channel output waveforms of different signal category. However, multi-path channel may cause seriously distortion. In the simple machine learning model, a small level of linear or nonlinear processing is applied to classify the input data. This kind of simple structure model can not fully learn the complex structure information from the distorted signal. Therefore, it is necessary to find a model that can fully represent the complex information from the muti-path channel output signal.

Deep learning [9], [10], [11], [12] is a novel machine learning method that can learn complex information by itself. In this paper, we propose a novel deep learning detection method for signal demodulation in short range multi-pathchannel. The proposed system consists of three modules: modulation, channel, and demodulation. The modulation module creates the modulated signals. The channel module adds noise, interference, and phase shifting to it. The demodulation module returns the detected transmitted bits type.

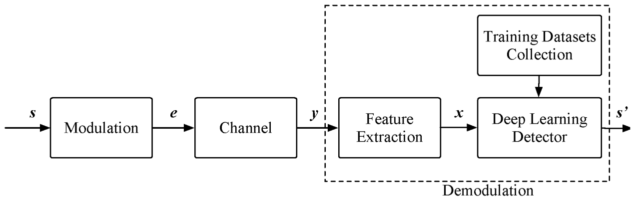


Figure 1. System structure

It is fulfilled by three processes, namely Training Datasets Collection, Feature Extraction and Deep Learning Detector. Feature Extraction extracts features from the channel out waveform. Deep Learning Detector detects the transmitted signal category. The parameters used in Deep Learning Detector is learned before the signal communication. The training datasets are collected by Train Datasets Collection.

The rest of the paper is organized as follows: Section II shows the system model and each process in system model. Section III gives a brief introduction of the deep learning structure. In Section IV, we present the simulation results under the condition of multi-path channel. Section V conclude the paper.

II. System Architecture

The system is composed of three modules: modulation, channel, and demodulation. The modulation module creates the modulated signals. The channel module adds noise, interference, and phase shifting to it. The demodulation module returns the detected signal category. The demodulation module is fulfilled by training datasets collection, feature extraction and deep learning detector. The detailed description of the system is illustrated in Fig. 1, in which the dashed rectangle shows the demodulation module.

A. Modulation

In this paper, we use binary phase shift keying (BPSK) as the modulation signal. The formula for BPSK is shown as follow:

$$\begin{aligned} e_0(t) &= cos(2\pi f_c t), \qquad 0 \le t < T \\ e_1(t) &= -cos(2\pi f_c t), \qquad 0 \le t < T \end{aligned} \tag{1}$$

where e_0 and e_1 indicate the modulated signals of bit category "0" and "1", respectively, f_c represents the carrier frequency, and $T = 1/f_c$ indicates the temporal length of a bit.

B. Channel

This paper simulates the system under the environment of short range multi-path channels. Multi-path is the propagation phenomenon that results in radio signals reaching the receiver by two or more paths. We generated the multi-channel environment by AR model. The composite signal at the channel output is given by:

$$y(t) = \sum_{\mathrm{i}=1}^{\mathrm{P}} \mathrm{a_i e(t - \tau_i) + noise(t)} \tag{2}$$

where P is the number of received paths, τ_i is the time delay of the $i-th$ path, a_i is the path gain of the $i-th$ path, and $noise(t)$ is i.i.d. standard Gaussian noise.

C. Demodulation

Due to multi-path effects and inter-symbol interference, the signal waveform outputted by multi-path channel is a distorted waveform compared to its modulated signal waveform. We cannot detect the transmitted signal category through its channel output signal waveform directly. The existed wireless communication system in short range multi-channel achieves signal demodulation by using a equalizer to minimize the effect of multi-path effects and inter-symbol interference before the signal detection. However, the channel equalization methods are either with high complexity or a waste of frequency resource.

To solve this problem, this paper proposes a novel deep learning based demodulation method. The proposed method does not need channel equalization process. We first extract features from the channel out waveform. Then we use a trained deep learning detector to detect the transmitted signal category. The train datasets that used to learn the parameters in the deep learning detector is collected by Training Datasets Collection process.

In this paper, we only consider the short distance communication system. We assume that the maximum time delay of each path does not exceed the temporal length of code T. Thus, the received signal in its temporal length contains most of the signal information. To extract features that can represent the signal information, Feature Extraction process samples the channel output waveform in its temporal length with sample frequency f_s as the feature of the transmitted signal. Then we use deep learning detector to detect the transmitted signal category based on the extracted feature. The deep learning detector consists of two main steps: Training and Testing. Training step is occurred before the signal communication. This step takes as input train datasets and returns the parameters of the deep learning model. The Testing step estimates the transmitted bit category using the feature extracted by feature extraction process. We will give a brief introduction of the deep learning model in section III. We next introduce how to collect the training datasets used to learn the parameters of the deep learning model.

1) Training Datasets Collection: Algorithm 1 shows the details of the training datasets collection process. It takes as input train bits number b, max number of received path P_{max}, loop number l_{max} and max delay t_{max}, where b is the train bits number for each channel environment, P_{max} is max number of the received paths in train channel, l_{max} is the number of train channel environments with per number of the received paths, and t_{max} is the max time delay used in train channel environment. It returns training datasets: training feature matrix $X \in \mathrm{R}^{m \times n}$ and correspondence category matrix $S \in \mathrm{R}_n$.

Algorithm 1: Training Datasets Collection

```
Input: b:the number of train bits for each channel; p_max:max
       number of received paths; l_max: loop times; d_max:max
       delay time;f_s: sampling frequency
Output: X: Training features; S: Training categories;
1  X = { ∅ }
2  S = { ∅ }
3  s = randi([0, 1], b)
4  e = modulate(s)
5  for each i ∈ [1, 2, . . . , p_max] do
6  |  for each j ∈ [1, 2, . . . , l_max] do
7  |  |  a = randn([0, 1], p_max)
8  |  |  τ = randn([0, d_max], p_max)
9  |  |  y = channel(e, a, τ)
10 |  |  x = feature(y)
11 |  |  X = X ∪ x
12 |  |  S = S ∪ s
13 return X, S
```

Algorithm 1 first randomly generates the train bits vector $s \in \mathrm{R}^b$, where $s_i \in [0,1]$ which will be used in each of the channel environment (line 3). Next it modulates the bits vector s to BPSK signals sequence with Equation 1 (line 4). Then it transmits signal sequence through different kinds of channel environments with each number of path (line 5). For each number of path, we generate l_{max} kinds of channel environments (line 6). For each channel environment, it randomly generates path gains $a \in \mathrm{R}^i$ and time delays $\tau \in \mathrm{R}^i$ (line 7-8). With the path gains $a \in \mathrm{R}^i$ and time delays $\tau \in \mathrm{R}^i$, where maximum value of a is 1, the maximum value of τ is d_{max}, it transforms the modulated signal with the transformation equation given by Equation 2 (line 9). Next, it extracts feature from the channel output waveform. The feature extraction process is fulfilled by sampling the channel output waveform with sample frequency f_s. The sampled data in the temporal length of the bit corresponds to its feature, which is the sampled matrix $x \in \mathrm{R}^{m \times p}$, where $m = f_s/f_c$ (line 10). Then, it collects x and s extracted from each channel environment (line 11-12). Finally, it returns the training features and correspondence categories.

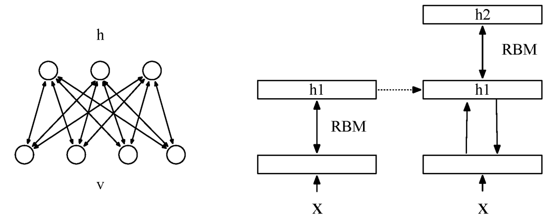
III. Deep Learning Model

We have introduced the demodulation module in section II. The deep learning model is one of the most important process in demodulation module. Based on our empirical experiments, we observe that the existing deep learning model Deep Belief Networks (DBN) and Stacked Auto-encoder (SAE) fit well in our system. DBN and SAE are proposed by Hinton et al. [9]. They greedily pre-train each layer using the previous layers activations as inputs, and then use back propagation algorithm to fine-tune the whole architecture subsequently. Apart from these two deep models, we also propose a novel deep learning model – Twice Training Network (TTN). This model can be used to detect the signals in short range multi-path channel

without estimation. Meanwhile, its complexity is lower than

DBN and SAE.

In the following we give a brief explanation of the three deep learning models.



(a) RBM (b) DBN generation

Figure 2. DBN model

A. Deep Belief Networks

As shown in Fig. 2, DBN is a deep learning model consisting of multiple Restricted Boltzmann machines (RBMs). The second RBM use the first RBMs hidden layer as the second RBMs visible layer. DBN trains a RBM on input to obtain its weight matrix and use this as the weight matrix between the lower two layers of the network. Then it transform the input by the RBM to produce new data anduse the new data as the input of the next pair of layers. We repeat the procedures until the top two layers of the network are reached. Finally, DBN fine-tunes all the parameters of this deep architecture with respect to a supervised training criterion.

The lower layer v, is defined as the visible layer, and the top layer h as the hidden layer. The visible and hidden layer units v and h are stochastic binary variables. The RBM model defines the probability distribution:

$$P(v) = \frac{1}{Z}\sum_{h} e^{E(v,h)} \tag{3}$$

where the energy function:

$$E(v,h) = -a^{\mathrm{T}}v - b^{\mathrm{T}}h - v^{\mathrm{T}}Wh$$
$$Z = \sum_{v,h} e^{E(v,h)} \tag{4}$$

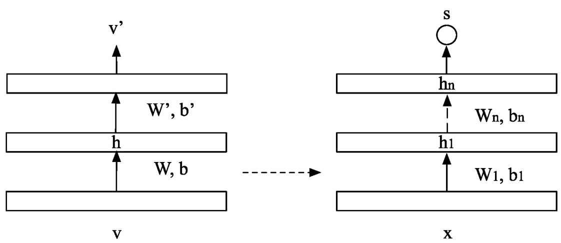
The objective of RBM is to learn the weights and the representation by maximizing the product of probabilities assigned to training sets V:

$$\arg\max_{\Theta} \prod_{v \in V} P(v)$$
$$\Theta = \{W, a, b\} \tag{5}$$

B. Stacked Auto Encoder

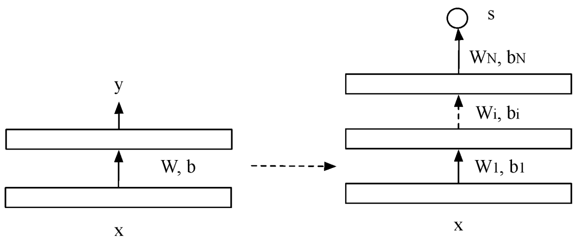
As shown in Fig. 3, SAE is a deep learning model consists of multiple layers of auto-encoders. It first trains the parameters of each auto-encoder layer individually. It then uses a global fine-tuning stage to backpropagate through the entire network for SAE structure. An auto-encoder consist of two parts: the encoder and the decoder. The encoder maps the input $v \in \mathrm{R}^m$ to the hidden layer $h \in \mathrm{R}^{m_1}$ via a nonlinear mapping:

$$h = s_e(W_1 v + b) \tag{6}$$



(*a*) Auto-encoder (*b*) SAE

Figure 3. SAE



(a) Reconstructor (b) TTN

Figure 4. TTF

where s_e is the activation function of the encoder e.g. *sigmoid* function, W and b are parameters where $W \in \mathrm{R}^{m\times m_1}$ is a weight matrix and $b \in \mathrm{R}^{m_1}$ a bias vector.

The decoder maps the hidden layer back to a reconstruction v' via another mapping function.

$$v' = s_d(W'h + b^0) \tag{7}$$

where s_d is the activation function of the decoder, $W_1{}^0$ and b^0 are parameters for decoder, where $W' \in \mathrm{R}^{m_1\times m}$ is a weight matrix and $b' \in \mathrm{R}^m$ is a bias vector.

For each input, we use loss function $l(v) = \|v - v'\|^2$. In order to train a single-layer autoencoder, we need to optimize the learning parameters to minimize the overall loss between inputs and their reconstructions:

$$\underset{\Theta}{\arg\min} \sum_{v\in V} l(v)$$
$$\Theta = \{W, W', b, b'\} \tag{8}$$

C. Twice Training Network

TTN consists of a pre-training process and a fine-tuning process. The objective of the pre-training process in TTN is to minimize the distance between the input and its template. We generate two kinds of templates according to the signal category. If the signal category is 1, we sample the modulated signal of bit "1" e_1 with sample frequency f_s as its template. Otherwise, we sample the modulated signal of bit "0" e_0 with sample frequency f_s as its template.

Fig. 4 shows the TTF model structure. We first learn the parameters associate to the Reconstructor shown in Fig. 4 (a). We use the template of a signal as the output of the network to train the weight,

$$t' = f(Wx + b) \tag{9}$$

where $W \in \mathrm{R}^{n\times n}$ is weight matrices, $h \in \mathrm{R}^n$ is bias vector, and

f is the active function

$$f(x) = \frac{1 - e^{-2x}}{1 + e^{2x}} \tag{10}$$

In order to train a single-layer network, we need to minimize the overall loss between inputs and outputs. For real valued x, squared loss is often used: $l(t) = \|t' - t\|$

$$\underset{\Theta}{\arg\min} \sum_{x\in V} l(t)$$
$$\Theta = \{W, b\} \tag{11}$$

Fig. 4 (b) shows the structure of TTN. Main components of TTN are: (1) a reconstructor layer that aims to reconstruct the signal vector to its template vector. This layer is initialized by training the re-constructor; (2) a set of fully connected hidden layers, which enables the signal vector to be linearly classified by making a spatial transformation. (3) a sigmoid layer that outputs probability scores reflecting that which category the channel output signal belongs to.

To detect the category of the input signal, we first use the parameters collected by the reconstructor above to initialize the parameters of the first layer. Then a global stage back propagates through the entire network to learn the weights of the whole network.

$$\begin{aligned} h_1 &= f(W_1x + b_1) \\ h_i &= f(W_ih_{i-1} + b_i), i = 2, \ldots, N-1 \\ s' &= f(W_Nh_{N-1} + b_N) \end{aligned} \tag{12}$$

For a training sequence x and the corresponding label $s \in [0,1]^m$, we minimize the overall loss by:

$$\underset{\Theta}{\arg\min} \sum_{s_l\in s} s_l log(s_l')$$
$$\Theta = \{W_i, b_i\}, i = 1, \ldots, N \tag{13}$$

IV. Performance

In this section, we conduct several simulations in multipath channels to validate the proposed methodology of binary signal classification proposed in Section II and Section III.

In our experiments, we use BPSK with carrier frequency $f_c = 25KHz$ as the modulated signal. In the feature extraction process and training datasets collection process, we use sampling frequency $f_s = 500KHz$. In the training datasets collection process, we use training bits number $b = 10000$ and max number of received paths $p_{max} = 7$ for each channel environment, and $l_{max} = 100$ kinds of environments for each path number. In each kinds of environment, the amplitude and time delay are randomly generated, where the maximum time delay is $d_{max} = 2 \times 10^{-5}$. The experiments reporting bit error rate (BER) is computed using 1×10^7 symbols, where the time delays and path gains are random generated.

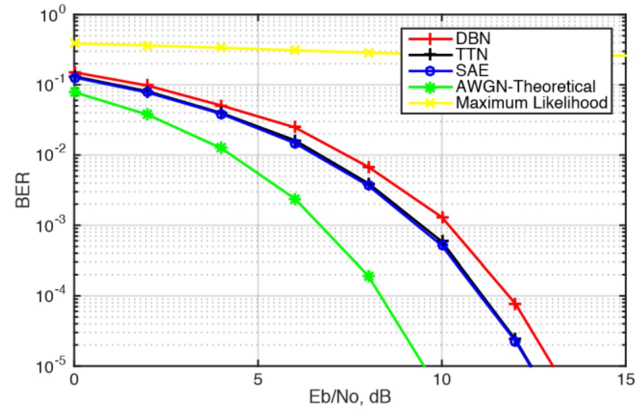


Figure 5. BER of the 3-path channel

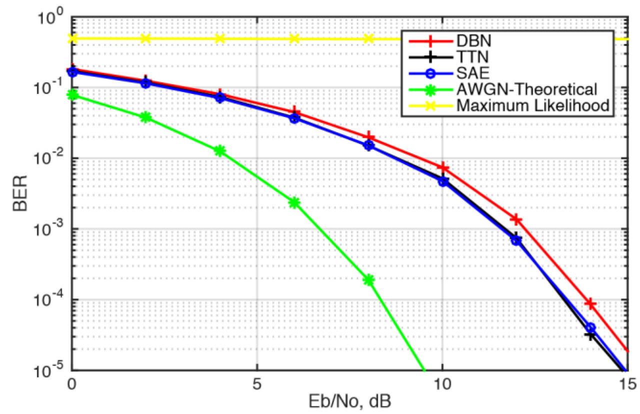


Figure 6. BER of the 5-path channel

Fig. 5 and Fig. 6 show the BER of 3 paths and 5 paths channel, respectively. It can been seen in Fig. 5 and Fig. 6, the proposed system with all deep learning based detectors can demodulate signals under the short range multi-path channel without channel equalization. From the results shown in Fig. 5 and Fig. 6, we observe that both TTN and SAE yield lower BER accuracy compared with DBN. Although the results of TTN and SAE are similar, the complexity of TTN is lower than SAE since TTN only have on layer in pre-training process while SAE has two layers. We also evaluate the performance of maximum likelihood method without channel equalization, results in Fig. 5 and Fig. 6 show that the maximum likelihood method cannot detect the signal without channel equalization in multi-path channel.

V. CONCLUSION

This paper propose a deep learning based detector for signal demodulation in short range multi-channels. The proposed demodulation method can demodulate signal without signal equalizer in short range multi-channel. The demodulation method in this paper is fulfilled by three processes of train datasets collection, feature extraction and deep learning detector. Deep learning detector consist of two steps of training and testing, in which training step is occurred before the signal communication. We have simulated the system with BPSK. Simulation experiments show the feasibility and superiority of our system.

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REFERENCES

[1] C.-S. Lim, K.-J. Lee, N.-J. Ku, D.-S. Hyun, and R.-Y. Kim, "A modularized equalization method based on magnetizing energy for a series-connected lithium-ion battery string," *IEEE Transactions on power Electronics*, vol. 29, no. 4, pp. 1791–1799, 2014.

[2] G. Das, P. K. Pattnaik, and S. K. Padhy, "Artificial neural network trained by particle swarm optimization for non-linear channel equalization," *Expert Systems with Applications*, vol. 41, no. 7, pp. 3491–3496, 2014.

[3] X. Li and H. Gao, "Reduced-order generalized filtering for linear discrete-time systems with application to channel equalization," *IEEE Transactions on Signal Processing*, vol. 62, no. 13, pp. 3393–3402, 2014.

[4] I. Kaya, E. Tugcu, A. Ozen, and A. R. Nix, "Fast convergence algorithm for blind channel estimation and equalization using cmf-dfe," in *Vehicular Technology Conference (VTC Spring), 2015 IEEE 81st*. IEEE, 2015, pp. 1–7.

[5] C. J. Bordin and M. G. Bruno, "Sequential bayesian algorithms for identification and blind equalization of unit-norm channels," *IEEE Signal Processing Letters*, vol. 22, no. 11, pp. 2157–2161, 2015.

[6] L. Xu, J. Chen, Y. Zhan, J. Lu, and D. Huang, "Robust blind channel equalization based on input decision information," in *Wireless Communications & Signal Processing (WCSP), 2013 International Conference on*. IEEE, 2013, pp. 1–6.

[7] X. Chen and L. Wu, "Nonlinear demodulation and channel coding in ebpsk scheme," *The Scientific World Journal*, vol. 2012, 2012.

[8] L. Fang, L. Wu, and Y. Zhang, "A novel demodulation system based on continuous wavelet transform," *Mathematical Problems in Engineering*, vol. 2015, pp. 1–9, 2015.

[9] G. E. Hinton and S. Osindero, "A fast learning algorithm for deep belief nets," vol. 18, no. 7, 2006, pp. 1527 – 1554.

[10] Y. Bengio, "Learning deep architectures for ai. foundations and trends," *Machine Learning*, 2009.

[11] I. Arel, D. C. Rose, and T. P. Karnowski, "Research frontier: deep machine learning–a new frontier in artificial intelligence research," *IEEE Computational Intelligence Magazine*, vol. 5, no. 4, pp. 13 – 18, 2010.

[12] M. Zeiler, G. W. Taylor, and R. Fergus, "Adaptive deconvolutional networks for mid and high level feature learning," *Proceedings*, vol. 24, no. 4, pp. 2018–2025, 2011.