A New Channel Coding Scheme with Machine Learning

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ABSTRACT

Nowadays, communication engineering field is getting more and more complex and mature, and researchers find it hard to improve the performance by applying expert knowledge. At the same time, deep learning shines in many domains such as computer vision and cyberspace security. An increasing number of researchers have recognized the potential application of deep learning to the physical layer.

We present and discuss a novel coding and modulation scheme with deep learning. It is considering a communication system as an autoencoder. The transmitter and receiver are composed of neural network layers. Then we train those deep neural network layers of the autoencoder and achieve excellent performance for encoding and decoding. In this thesis, we show how to build an end-to-end learning of communication system based on neural networks, and compare the performance of it with the traditional communication schemes (QPSK and BPSK). We also present a discussion of some open research challenges in this area and several kinds of future work needed to be done.

BACKGROUND

- In the field of communication engineering, researchers have tried to extend machine learning and deep learning towards communication area in the past, but they rarely focus on physical layer. Machine learning did not cause any fundamental impact on the physical layer. The main reason is that when designing and implementing communication systems, we mainly model the system based on information theory, statistics and signal processing. As long as the system model could fully fit the real-world conditions, we could design an extremely accurate communication system and achieve perfect performance. And then we could implement a powerful algorithm for symbol detection.
- We believe that deep learning could yield significant improvements on the communication engineering. The author in [1] presented a completely new way to design communication system in the physical layer. It is considering a communication system as an autoencoder. We could use deep learning theory to train those deep neural network layers of the autoencoder and achieve excellent performance for encoding and decoding. In this thesis, we would simulate the autoencoders of [1] and evaluate the performance of those. We also present the representation of the autoencoder with higher dimension, and discuss the problem of representation of the autoencoder.

REFERENCE

- [1] T. J. O'Shea and J. Hoydis. (2017) An introduction to deep learning for the physical layer. [Online]. Available: https://arxiv.org/abs/1702.00832, preprint.
- [2] F. Chollet. (2015). Keras. [Online]. Available: https://github.com/fchollet/keras

METHODOLOGY

- Neural Networks
- Traditional Communication System
- Communication System based on autoencoder

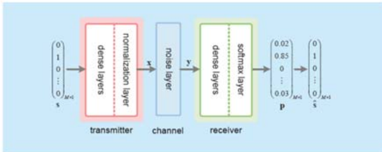

Figure 5.2: A simple autoencoder for an end-to-end communication system.

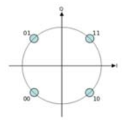

Figure 3.1: The constellation diagram of QPSK

A feedforward Neural Network with L layers is to describe a mapping $f(\boldsymbol{r_0};\boldsymbol{\theta}) : \mathbb{R}^{N_0} \mapsto \mathbb{R}^{N_L}$, which is an input vector $\boldsymbol{r_0} \in \mathbb{R}^{N_0}$ to an output vector $\boldsymbol{r_L} \in \mathbb{R}^{N_L}$, and there are through L iterative processing steps:

$$r_l = f(\boldsymbol{r_{l-1}};\boldsymbol{\theta}_l),\ l = 1, ..., L \tag{4.1}$$

where $f(\boldsymbol{r_{l-1}};\boldsymbol{\theta}_l) : \mathbb{R}^{N_{l-1}} \mapsto \mathbb{R}^{N_l}$ is the mapping carried out by the lth layer. This mapping depends on the output vector r_{l-1} and a set of parameters $\boldsymbol{\theta_l}$. This work presents that $f(\boldsymbol{r_{l-1}};\boldsymbol{\theta}_l)$ has the form

$$f(\boldsymbol{r_{l-1}};\boldsymbol{\theta}_l) = \sigma(\boldsymbol{W_l} \boldsymbol{r}_{l-1} + \boldsymbol{b}_l) \tag{4.2}$$

the lth layer is called *dense* or *full-connected* layer, where $\boldsymbol{W}_l \in \mathbb{R}^{N_l} \times \mathbb{R}^{N_{l-1}}, \boldsymbol{b}_l \in \mathbb{R}^{N_l}$, and $\sigma(\cdot)$ is an *activation* function, and $\boldsymbol{\theta}_l = \{\boldsymbol{W}_l, \boldsymbol{b}_l\}$. Common activation functions and layer types are listed in Table. 4.1 and Table. 4.2 respectively.

This thesis uses labelled training data to train neural networks. For instance, the labelled data is a set of input and output vector pairs $(\boldsymbol{r}_{0,i}, \boldsymbol{r}^*_{L,i}), i = 1, ..., S$, where $\boldsymbol{r}^*_{L,i}$ is the desired output vector and $\boldsymbol{r}_{0,i}$ is the input vector.

The training process is mainly to reduce the loss to minimum value:

$$\boldsymbol{L}(\boldsymbol{\theta}) = \frac{1}{S}\sum_{i=1}^{S} l(\boldsymbol{r}^*_{L,i}, \boldsymbol{r}_{L,i}) \tag{4.3}$$

RESULTS

- Constellations of Autoencoders with different parameters
- BLER versus Eb/N0 for Autoencoders with different parameters
- BLER versus Eb/N0 for different autoencoders and traditional systems

RESULTS

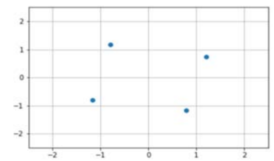

Figure 7.1: Constellations of Autoencoder $(2, 2)$

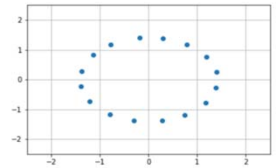

Figure 7.2: Constellations of Autoencoder $(2, 4)$

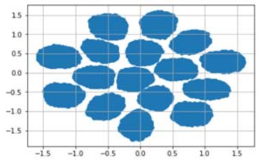

Figure 7.3: Constellations of Autoencoder $(7, 4)$

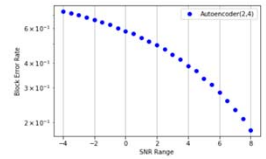

Figure 7.5: BLER versus E_b/N_0 for Autoencoder $(2, 4)$

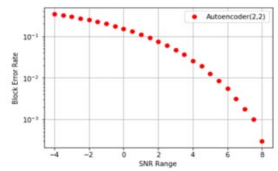

Figure 7.4: BLER versus E_b/N_0 for Autoencoder $(2, 2)$

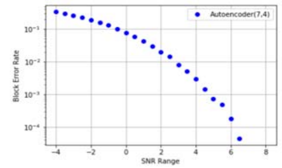

Figure 7.6: BLER versus E_b/N_0 for Autoencoder $(7, 4)$

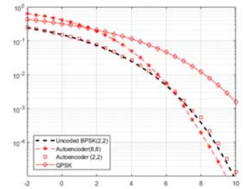

Figure 7.7: BLER versus E_b/N_0 for different autoencoders and traditional systems

CONCLUSION AND FUTURE WORK

- Autoencoders could achieve competitive BLER performance compared with traditional communication systems.
- However, there is a problem. To train and represent autoencoder with higher dimension remain a challenge.
- For now, it is a promising research area and far from maturity. A wide range of studies into DL for physical layer is needed to be done, and we believe researchers would conduct further studies in this promising area, including theoretical analysis, implementation in real-world scenarios.