M.S. THESIS

Deep Learning-aided Spreading Sequence Design for Massive Machine-Type Communications

사물 통신에서 딥러닝을 이용한 확산코드 설계

BY

KIM DONG WOO

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이 논문을 공학석사 학위논문으로 제출함

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김동우의 공학석사 학위 논문을 인준함

2019년 8월

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Abstract

Massive machine-type communications (mMTC) have been drawing a lot of attentions because the number of MTC devices is expected to be increasing in the next generation (5G) communication systems with a variety of Internet-of-Things (IoT) applications. For effective uplink transmission in the mMTC, the grant-free non-orthogonal multiple access (NOMA) scheme has been a promising solution to overcome high signaling overhead and latency problems. Due to instant transmissions, active user detection (AUD) is an important task for grant-free NOMA.

In the transmitter, data symbols are spread by user-specific spreading sequences. However, the most research papers have focused on designing the effective detection algorithms, but not given much attention to the transmitter design. In this dissertation, the generation of spreading sequences via deep learning is proposed. With sufficient training data, the proposed spreading sequences show the close performance to the mathematically optimized sequences. In particular, we show the capabilities of learning sequences by demonstrating that learned sequences can have different cross-correlations depending on the activity probability of each user.

keywords: Massive machine-type communications, compressed sensing, non-orthogonal multiple access, active user detection, deep learning, spreading sequence.

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Contents

Abstract **i**

Contents **ii**

List of Tables **iv**

List of Figures **v**

1 Introduction **1**

2 System Model **4**

3 Design of Spreading Sequences using Deep Learning **6**

3.1 Entire Network Structure of the System 6

3.2 Spreading Layer 7

3.3 Active User Detection Layer 7

4 Simulation Results **12**

4.1 Simulation Setup 12

4.2 Simulation Results and Interpretation 13

5 Conclusion **19**

Abstract (In Korean) **22**

Acknowlegement **23**

List of Tables

4.1 Average and maximum cross-correlations 17

List of Figures

3.1 The brief structure of the entire neural networks. 10

3.2 The structure of active user detector. 11

4.1 AER as a function of SNR (dB). 15

4.2 AER as a function of activity probability. 15

4.3 Histogram of the absolute cross-correlation between the random sequences. 16

4.4 Histogram of the absolute cross-correlation between the optimized sequences. 16

4.5 Histogram of the absolute cross-correlation between the proposed sequences. 17

4.6 AER with heterogeneous activities. 18

4.7 Average cross-correlations with heterogeneous activities. 18

Chapter 1

Introduction

Machine-type communications (MTC) is communications where MTC devices interact with a server or other MTC devices without human interaction. Recently, with a wide range of Internet-of-Things (IoT) applications such as manufacturing and healthcare, the number of MTC devices has been increasing. In accordance with this trend, massive machine-type communications (mMTC) has been one of the services that International Telecommunication Union (ITU) expects to be the main scenario in fifth generation (5G) wireless systems [1]. The mMTC focuses on supporting uplink communications with the massive number of MTC devices to the base station.

As the conventional multiple access schemes allocate orthogonal radio resources to each user and use grant-based transmission, it is inappropriate for the mMTC. To overcome high signaling overhead and latency problems, grant-free non-orthogonal multiple access (NOMA) has been proposed [2]. In grant-free NOMA, MTC devices or users transmit non-orthogonal signals without a complicated scheduling procedure. Due to instant transmissions, the base station is not aware of the identification information. Accordingly, efficient active user detection (AUD) before data detection is necessary for the grant-free NOMA.

The compressed sensing techniques can help to detect active users because users transmit data sporadically in mMTC. In other words, the transmitted signal can be modeled as a sparse vector. Thus, the AUD problem can be considered as the sparse vector recovery problem which the compressed sensing mainly aims to solve. Recent studies have worked on compressed sensing based active user detection schemes. In [3], [4], correlation-based greedy algorithms are applied to detect active users. In addition, deep neural network (DNN)-based approaches have been proposed for sparse vector recovery problem. In [5], the DNN structure which is based on the iterative hard thresholding was proposed.

The most papers have focused on developing the effective detection algorithms, but not given much attention to the transmitter design. As mentioned, each user is allocated non-orthogonal radio resources. In other words, each symbol is spread by different spreading sequences in the transmitter. In [3], [4], [5], the randomly generated spreading sequences are used for convenience. On the other hand, the algorithms to choose the optimal matrix have been proposed in the compressed sensing literature [6], [7]. The optimality condition is for designing the matrix having low-correlated columns. However, the optimized sequences with the condition cannot guarantee optimality in terms of the signal reconstruction performance. Furthermore, both the random and optimized sequences cannot reflect the side information of activity probabilities which are the probabilities that users transmit symbols.

To overcome these drawbacks, we resort to deep learning (DL). In the recent decade, DL has received a great deal of attention in domains such as natural language processing and computer vision because DL can solve very complicated optimization problems. In applications which are very difficult to characterize with mathematical models, DL is powerful at modeling because neural networks can represent a variety of functions when the parameters of neural networks are properly learned. It is very difficult to find the mathematical model for optimizing the spreading sequences which achieve the best AUD performance. Representing the entire system of the transmitter and receiver with a DNN, we find the spreading sequences which are learned in the direction of minimizing AUD error. In addition, the spreading sequences can be learned to involve the activity probabilities by data-driven fashion.

An aim of this dissertation is to propose a technique that generates user-specific spreading sequences through DL. Existing compressed sensing-based active user detection schemes use the random sequences or the optimized sequences with low correlation on the transmitter. These sequences cannot guarantee the optimality in terms of the AUD performance and reflect the activity probability of each user. To tackle these challenges, we introduce a DNN as an alternative to represent the entire system which consists of the signal spreading, channel, and the receiver. In the transmitter, the spreading process can be replaced with a trainable neural layer. In the receiver, AUD is performed by fully-connected neural networks (FCNNs). After training, weight parameters in the transmitter is used as the learned spreading sequences. Through end-to-end training, spreading sequences can be learned to achieve the best AUD performance. From numerical experiments, we interpret what the proposed sequences learned and show the difference with the optimized sequences. We show that the proposed sequences outperforms the random sequences. In the system with heterogeneous activities, the proposed sequences shows slightly better performance in comparison with the optimized sequences in the high signal-to-noise ratio (SNR) regime. Further, we show that the proposed sequences can be automatically learned to reflect the activity probabilities so that sequences have different cross-correlations depending on the activity probabilities.

The rest of the dissertation is organized as follows. Chapter 2 describes the system model. In Chapter 3, we discuss the design of spreading sequences using DL in details. In Chapter 4, we represent the numerical results and discuss interpretation. We finally conclude our paper in Chapter 5.

Notation: Boldface lower and upper-case characters represent column vectors and matrices, respectively. For a vector $\mathbf{x}$, x_i denotes its *i*th element. and $\mathbf{x}^\mathbf{T}$ its transpose.

Chapter 2

System Model

We consider the uplink transmission from *N* MTC devices or users with the base station. Traffic has an unpredictable and sporadic pattern, making the symbol vector $\mathbf{x} = [x_1, x_2, \cdots, x_N]^T \in \mathbb{C}^N$ a sparse vector. We assume that users are synchronized in time, meaning that all users transmit symbols and switch activity in the same time slot basis. Active users transmit just a single symbol in one time slot. In the transmitter, each symbol is spread by user-specific spreading sequences $\mathbf{s}_n = [s_1, s_2, \cdots, s_M]^T \in \mathbb{R}^M$ for *n*-th user, which the base station knows and uses to distinguish users. In this setup, the received signal at the base station can be formulated as

$$\mathbf{y} = \sum_{i=1}^{N} \mathbf{s}_i x_i + \mathbf{w} = \mathbf{S}\,\mathbf{x} + \mathbf{w}, \tag{2.1}$$

where $\mathbf{S} = [\mathbf{s}_1,\, \mathbf{s}_2, \cdots \mathbf{s}_N] \in \mathbb{R}^{M \times N}$ is the spreading matrix having columns of the corresponding spreading sequences and $\mathbf{x}$ is the symbol vector from all users. We assume that each symbol is uniformly chosen from a finite Alphabet $\mathcal{A}$ which includes zero for inactive users. User activity follows the i.i.d. Bernoulli distribution with an activity probability of p_n. $\mathbf{w}$ is the additive Gaussian noise vector with the noise variance σ_w^2 and fading channels are neglected for simplicity. In the mMTC scenarios, the number of resources *M* is smaller than the number of users *N*. The signals $\mathbf{s}_i x_i$ are non-orthogonal and the system becomes under-determined. Although it is not possible to find the solution of the under-determined system through the general ways such as linear least squares or minimum mean square error methods, the compressed sensing theorems say that $\mathbf{x}$ can be reconstructed from $\mathbf{y}$ under the condition that $\mathbf{x}$ is sparse enough [8].

Chapter 3

Design of Spreading Sequences using Deep Learning

3.1 Entire Network Structure of the System

In this section, we explain the generation of spreading sequences using DNN. In order to generate the spreading sequences, the transmitter and the receiver are merged into a neural network structure. Through an end-to-end training, weight parameters of the entire system are optimized simultaneously to minimize the loss function which is the AUD error. As an advantage of this autoencoder structure, the AUD performance is directly used in the generation of the spreading sequences. The stochastic gradient descent (SGD) is used to minimize the loss function and the weight parameters in the transmitter are also updated in the direction of minimizing the loss function. In addition, the spreading sequences can learn activity probabilities by exploiting those statistics information which is implicit in training data samples. The brief block diagram of the entire system is illustrated in Fig. 3.1.

In the transmitter, the modulated symbol vector $\mathbf{x}$ are spread by the spreading matrix $\mathbf{S}$. Instead of using the deterministic spreading, we consider spreading as a trainable mapping function from the symbol vector $\mathbf{x}$ to the transmitted vector $\mathbf{Sx}$. We call the hidden layer the spreading layer. The spreading layer can be denoted as $f(\mathbf{x}\,;\,\mathbf{S})$ with the trainable weight parameters $\mathbf{S}$. In the channel layer, the transmitted signal is affected by Gaussian noise. Finally, the symbol vector $\mathbf{x}$ is reconstructed from the received signal $\mathbf{y}$ in the receiver. AUD also can be considered as a mapping function from the received signal $\mathbf{y}$ to the support prediction vector $\mathbf{\Omega}_{pred} = [\delta'_1, \delta'_2, \cdots, \delta'_N]^T$, where $\delta'_n \in (0, 1)$. We call the hidden layers which detect active users the AUD layer. After AUD, inactive positions of the symbol vector $\mathbf{x}$ can be neglected and the system becomes over-determined. The actual data symbols are reconstructed by solving a least squares problem. In this work, we consider only up to the AUD, not the data detection for simplicity.

3.2 Spreading Layer

In uplink NOMA, users are distinguished by employing user-specific spreading sequences. Basically, the spreading processing is a linear mapping function from $\mathbf{x}$ to $\mathbf{S}\mathbf{x}$. As a primitive approach, we propose a single neural layer as

$$f(\mathbf{x}\,;\,\mathbf{S}_\theta) = \mathbf{S}_\theta \mathbf{x}, \tag{3.1}$$

where $\mathbf{S}_\theta$ is weight parameters. Because the neural layer does not have the non-linear activation and the bias parameter, the mapping function is linear in the same way as the conventional spreading is. The learned weights $\mathbf{S}_\theta$ are taken and used as spreading sequences after training.

3.3 Active User Detection Layer

The goal is to generate the spreading sequences to minimize AUD error. The learning of the spreading sequences should directly relate to the AUD performance. Therefore, we need to replace the active user detector with a neural network so that the gradient of loss function (AUD error) can be backpropagated to the spreading layer during training.

The AUD layer finds the non-zero positions of the symbol vector $\mathbf{x}$, given the noisy received signal $\mathbf{y}$. The non-zero positions are denoted by the support vector $\mathbf{\Omega}$. To estimate the support vector $\mathbf{\Omega}$ is a mapping function which outputs the probabilities of users being active. To this end, we use a fully-connected neural network (FCNN) as the probabilistic detector: $g: \ \mathbf{y} \rightarrow \mathbf{\Omega}_{pred} \in (0,1)^N$. Using sigmoid activation after the last hidden layer, the output of AUD layer is squashed as a vector in the range (0, 1). In addition, as inferring whether users are active or inactive can be considered as multi-label classification, the binary cross entropy is a natural choice for the loss function. The weight parameters θ of the entire neural network are determined by solving the following optimization.

$$\min_{\theta} \sum_{n=1}^{N} L_n, \tag{3.2}$$

$$L_n = -\big(\delta_n \log(\delta'_n) + (1-\delta_n)\log(1-\delta'_n)\big), \tag{3.3}$$

where L_n is the binary cross entropy of *n*-th user and δ'_n are δ_n are the elements of the predicted support vector $\mathbf{\Omega}_{pred}$ and the true support vector $\mathbf{\Omega}_{true}$ respectively.

It is important to use the improved structure for sparse vector recovery because the performance of the simple FCNN structure is not satisfactory. Various neural network structures have been proposed for sparsity enforcing problem. We introduce and improve the structure based on the iterative hard thresholding network (IHT-net) [5]. The original IHT is basically an iterative algorithm which refines the sparse signal estimate as updating the following step iteratively,

$$x^{(t+1)} = H_k[(I - \Phi^T\Phi)x^{(t)} + \Phi^T y], \tag{3.4}$$

where Φ is the system matrix and H_k is the nonlinear thresholding operation. In IHT-net, iterations are unfolded and each step is considered as a neural network layer which does not share weight parameters as the following expression

$$x^{(t+1)} = \mathrm{ReLu}[\Psi^{(t)}x^{(t)} + \Gamma^{(t)}y], \tag{3.5}$$

where thresholding is replaced with a rectified linear unit (ReLu) activation and $\Psi^{(t)}$ and $\Gamma^{(t)}$ are trainable weights of t-th layer. In [5], IHT-net shows improved performance compared to IHT. Based on IHT-net, we modified the architecture by expanding the width of each layer into 5 times N for effective sparse vector reconstruction and adding batch normalization layers. The structure of AUD layer is illustrated in Fig.3.2.

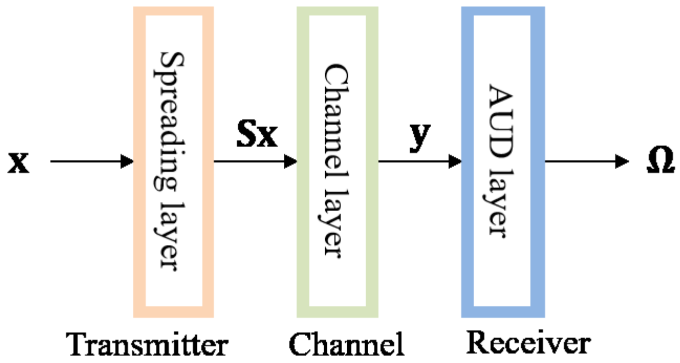

Figure 3.1: The brief structure of the entire neural networks.

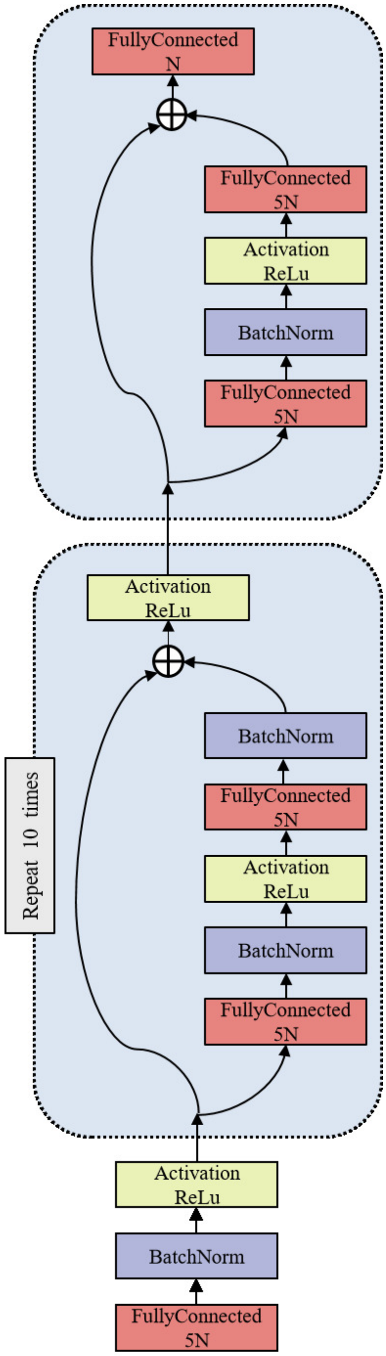

Figure 3.2: The structure of active user detector.

Chapter 4

Simulation Results

4.1 Simulation Setup

As a simulation setup, we simulate the uplink of the mMTC system with N = 64 users and M = 32 dimensional spreading sequences. Each spreading sequence is scaled as $\|\mathbf{s}_n\|_2 = 1$. As a first step, the activity probability p_n is set to be constant for all users. We also consider the practical system with users having different activity probabilities, which is called the system with heterogeneous activities. Data symbols of active users are modulated with binary phase shift keying (BPSK).

In order to compare the proposed sequences, we use the Gaussian random sequences and the optimized sequences [7]. As a performance measure, we use the activity error rate (AER) which considers both missed detections and false alarms. AER is defined as

$$\text{AER} = 1 - P\left(\frac{\mathbf{\Omega}_{true} \cap \mathbf{\Omega}_{pred}}{\mathbf{\Omega}_{true} \cup \mathbf{\Omega}_{pred}}\right). \tag{4.1}$$

As a training procedure, the symbol is randomly generated and the noise is also randomly generated and added to the transmitted signal. While there is no obvious theoretical research about SNR where training should be trained, we have observed the model trained at SNRs between 15 and 20 dB led to the good performance across wide ranges of SNR at testing. We used 480,000 different samples with 40 epochs for training, 60,000 samples for validation, and 60,000 samples for testing with batch size 200. We adopted Adam optimizer for SGD optimization. We reduced the learning rate by 10 times after 10 epochs, starting from 0.01.

4.2 Simulation Results and Interpretation

Fig. 4.1 shows the AER performance when p_n is 0.06. The model was trained at SNR of 15 dB. The random sequences perform worse than both the optimized and proposed sequences because the randomly generated spreading matrix have highly correlated columns. We observe that the proposed spreading sequences performs close to the optimized sequences.

In Fig. 4.2, we show the AER performance with the activity probability p_n which varies from 0.01 to 0.1 with fixed SNR of 15 dB. The model was trained at SNR of 15 dB. We observe that as p_n increases, the AER performance is degraded for all schemes. Note that while AUD with the proposed sequences shows close performance to the AUD with the optimized sequences, the proposed sequences achieves the slightly worse performance when p_n is low.

For understanding the behavior of sequences, we show the histograms of absolute cross-correlation of sequences in Fig. 4.3, 4.4, and 4.5. Additionally, table. 4.1 shows the average and maximum absolute cross-correlations of different cases. Absolute cross-correlation between sequences for ith and jth users is defined as $\mu_{i,j} = \left|s_i^T s_j\right|$ with $i \neq j$. It is seen from the histograms and table that the random sequences have the relatively high average and maximum cross-correlations compared to the other cases. We observe that the optimized sequences are the result of minimizing the maximum cross-correlation. On the contrary, It is interesting to note that learning the sequences leads to the effect of minimizing average cross-correlation. We can interpret that sequences having low average cross-correlation lead to close performance to the optimized sequences, even with moderately high maximum cross-correlation.

Thus far we have used the constant p_n for all users in comparing AER performance of the proposed sequences. Here, we ask if the learning of sequences can provide activity-specific sequences and improve AER performance when users have different p_n, namely the system with heterogeneous activities. We show that the AER performance under the system with different p_n in Fig. 4.6. The models were trained at SNR which was between 15 and 20 dB for each batch. p_n of each user is determined by the uniform distribution on the interval [0.01, 0.25] for case 1 and [0.01, 0.15] for case 2. We observe that the proposed sequences achieve about 100% gain over the coneventional sequences(optimized sequences) in case 1 and 40% gain in case 2 at SNR of 20 dB. We can interpret that the distribution yieding large deviation between activities leads to more performance gain when using proposed sequences. In Fig. 4.7, we plot the average cross-correlation of each user, which is defined as

$$\mu_{i,avg} = \frac{1}{N-1} \sum_{j=1}^{N} \left| \mathbf{s}_i^T \mathbf{s}_j \right| \ \text{ with } i \neq j \ . \tag{4.2}$$

Note that the frequently active users are assigned sequences with low cross-correlation against other sequences. This result implies that the sequences learned the implicit statistic of training data.

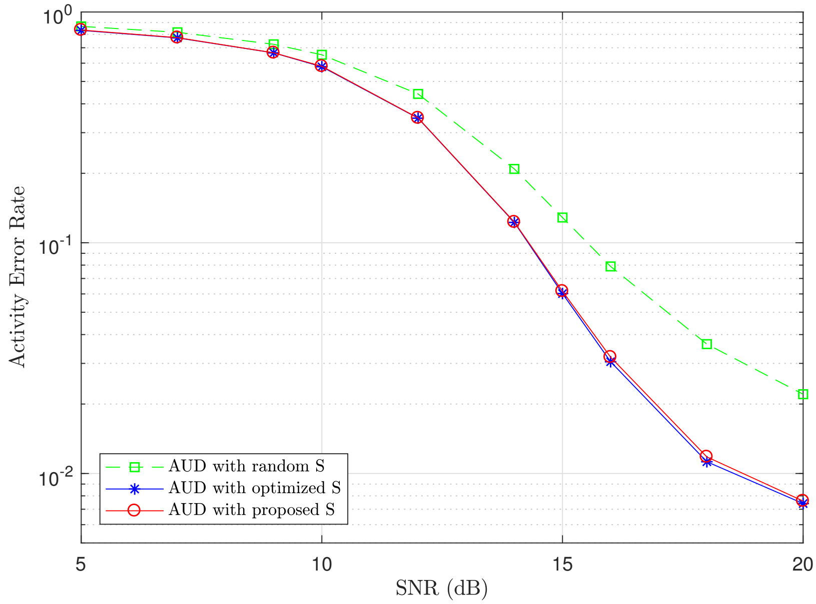

Figure 4.1: AER as a function of SNR (dB).

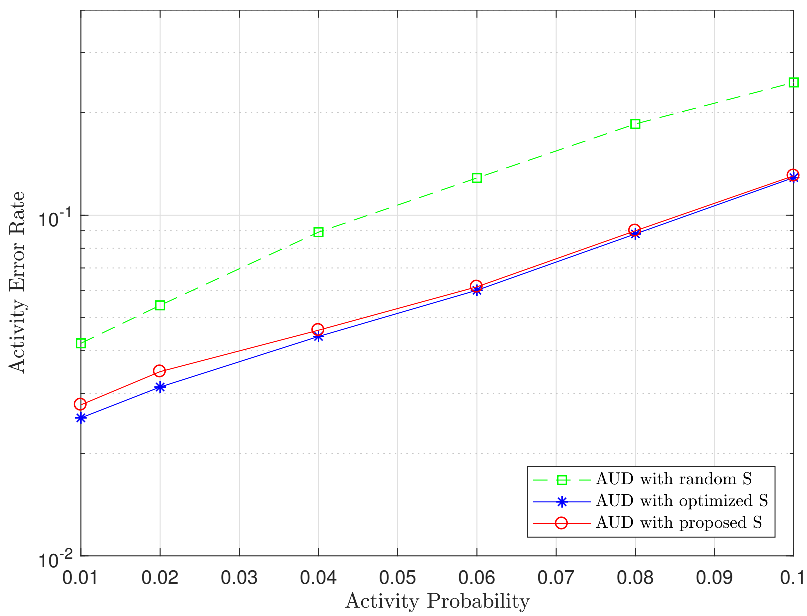

Figure 4.2: AER as a function of activity probability.

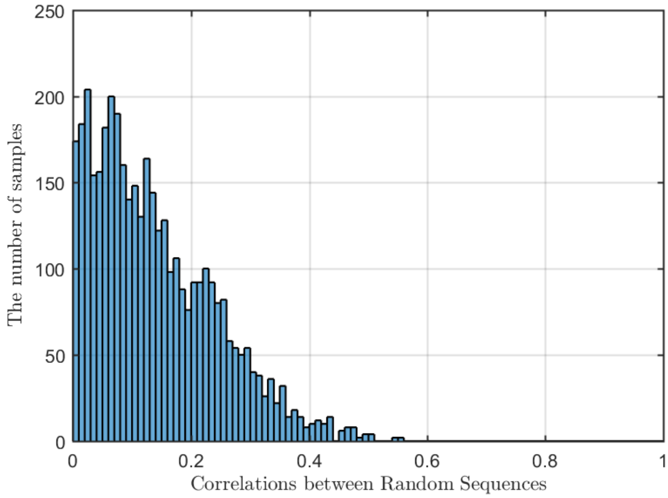

Figure 4.3: Histogram of the absolute cross-correlation between the random sequences.

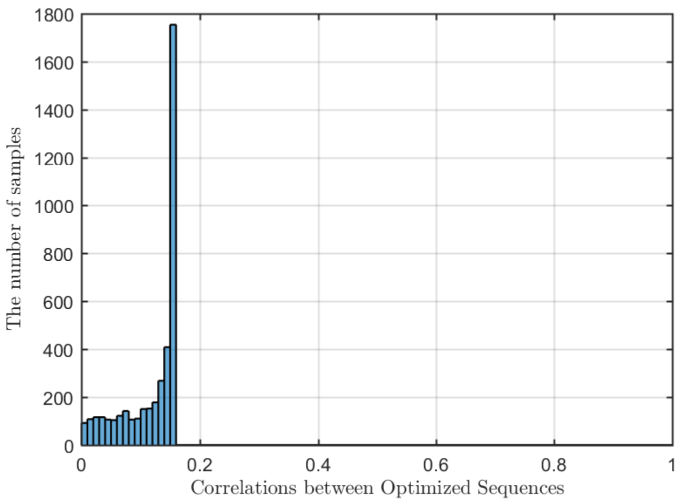

Figure 4.4: Histogram of the absolute cross-correlation between the optimized sequences.

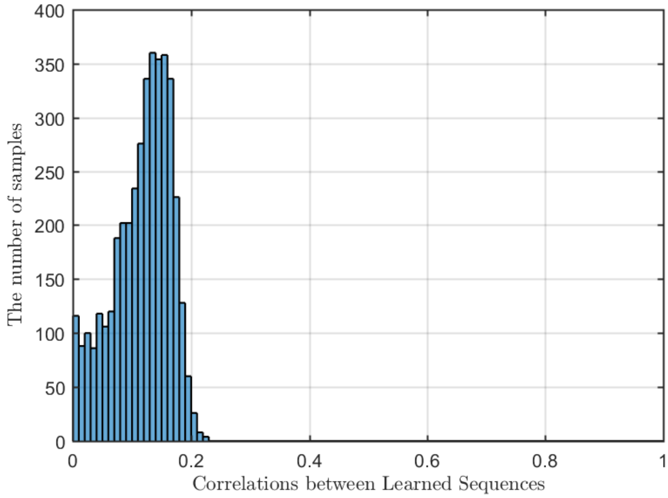

Figure 4.5: Histogram of the absolute cross-correlation between the proposed sequences.

Table 4.1: Average and maximum cross-correlations

Benchmarks	μ_{avg}	μ_{max}
RANDOM SEQUENCES	0.1407	0.5562
OPTIMIZED SEQUENCES	0.1176	0.1515
PROPOSED SEQUENCES	0.1162	0.2211

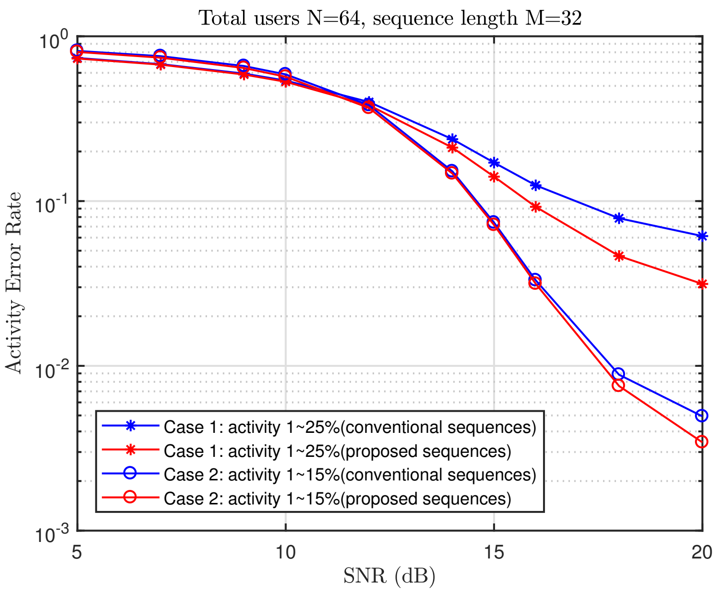

Figure 4.6: AER with heterogeneous activities.

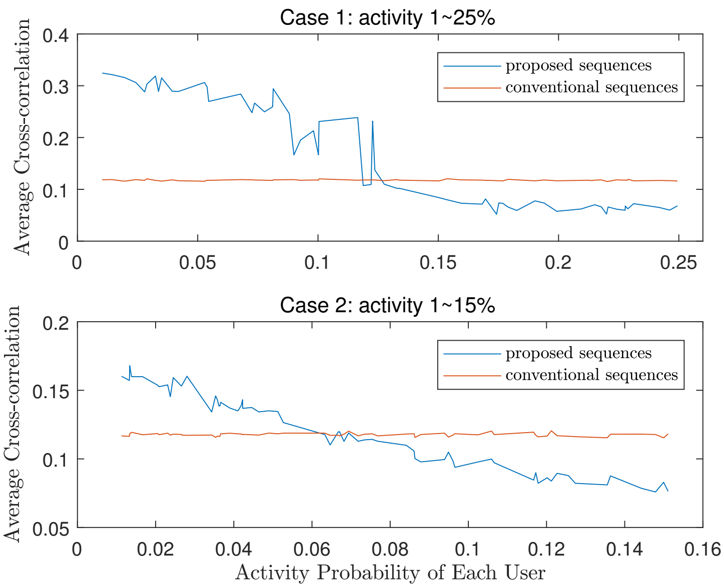

Figure 4.7: Average cross-correlations with heterogeneous activities.

Chapter 5

Conclusion

In this dissertation, a DL-aided spreading sequence design technique was proposed to support the uplink transmission of massive number of MTC devices for mMTC. DL enables the end-to-end learning of the entire system and the generation of sequences is able to directly exploit the AUD performance. In particular, we have shown that the spreading sequences can be generated depending on the activity probability p_n. For the system with uniformly distributed activity probabilities, small gain was achieved in high SNR regime only. Nevertheless, it suggests that DL can be an alternative method of generating spreading sequences for mMTC. There are open problems for further analysis of the capabilities of the learning of sequences. First off, other activity patterns or distributions should be analyzed to achieve more gain in the wide range of SNRs. Besides, the architecture of the spreading layer can be improved because a simple linear layer was deployed in this work.

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초록

5세대 이동통신에서 사물 통신기기들의 수가 폭발적으로 증가할것이라 예상되면서, 대규모 사물 통신(massive machine-type communications, mMTC)은 많은 관심을 받고있다. 효과적인 상향링크를 위해서 최근 무허가 방식의 비직교 다중접속(non-orthogonal multiple access, NOMA) 기술이 높은 신호 오버헤드와 지연 시간 문제를 해결하기 위한 대안으로 주목받고 있다. 특히 무허가 비직교 다중접속에서는 스케줄링 없이 즉각적인 전송이 이루어지기 때문에 활성 기기 검출(active user detection, AUD)이 중요한 문제가 된다.

대규모 사물 통신의 상향링크에서 송신기는 데이터 심볼에 기기마다 다른 확산 코드(spreading sequence)를 이용해 데이터를 확산해서 보낸다. 그러나 대부분의 기존 연구들은 수신기의 검출 알고리즘 연구에 치우쳐져 있고 송신기에서 어떠한 확산 코드를 설계해서 보내야 하는지는 미흡했다. 본 논문에서는 딥러닝을 기반으로 확산 코드를 설계하는 기법을 제안한다. 충분한 학습 데이터을 이용해서 학습된 확산 코드는 수학적으로 상관 관계가 최적화된 확산 코드와 비슷한 활성 기기 검출 성능을 보여주었다. 특히 기기들이 서로 다른 활성 확률을 가지는 환경에서는 확산 코드가 활성 확률에 따라 서로 다른 상호상관관계을 가지도록 학습되고, 높은 SNR에서 약 1.4배에서 2배의 성능의 향상을 보여준다.

주요어: 대규모 사물 통신, 압축 센싱, 비직교 다중접속, 활성 기기 검출, 딥러닝, 확산 코드

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