Deep Learning-Based Space Shift Keying Systems

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Abstract. To handle the performance degradation of space shift keying (SSK) systems under practical non-Gaussian channels, we propose a deep neural network model in which an auto-encoder (AE) is developed to design proper constellations and corresponding demodulation. With full knowledge of channel statistics, the transmitter and receiver are jointly optimized in our scheme. By representing the SSK system as an AE, we consider the cross-entropy loss function for antenna index and formulate the overall pipeline using deep learning techniques. Moreover, our implementation can be adopted in several noise conditions successfully. Results confirm that our model outperforms the maximum likelihood (ML) detection scheme in terms of block error rates (BLER).

Keywords: Space shift keying (SSK) · Deep learning · Neural network

1 Introduction

With the increasing varieties of communication scenarios, information transmission at high speed and reliability has become a main design goal in current communication systems [1]. Owing to the diversity and multiplexing gain in different transmission paths, research on multiple-input multiple-output (MIMO) system has aroused much attention. Spatial modulation (SM) is one promising MIMO techniques that transmits data symbol only on one antenna selected from an antenna group at each time slot [2,3]. When the antenna transmits a pulse instead of a symbol, SM reduces to space shift keying (SSK), in which the information is transmitted only by the index of the activated antenna. In SSK, only one antenna is activated at each transmission and thus only one radio frequency (RF) chain is required. Meanwhile, the problem of inter-channel interference (ICI) is circumvented naturally.

In SM and SSK systems, AWGN is usually considered as the channel model, whose closed-form expression can be explained as mathematical analytic formula directly. Consequently, the design of receiver discrimination schemes is simplified, leading to improvement of algorithm effectiveness. With full knowledge of

Supported by the National Key Research and Development Program of China (Grant No. 2017YFE011230).

S. Han et al. (Eds.): AICON 2019, LNICST 286, pp. 70–78, 2019.
https://doi.org/10.1007/978-3-030-22968-9_7

channel statistics, maximum likelihood (ML) detection scheme can demodulate the index of the activated antenna at the receiver side. The optimal transmitted bit streams can be recovered based on the code book. In practical communication scenarios, however, with the coexistence of complex interferences such as filtering, channel fading and other non-linear effects, the channel noise deviates from Gaussian distribution and exhibits non-Gaussian characteristics [4]. Motivated by the irritable performance degradation [5], the SSK system under such non-Gaussian practical channels requires much investigation.

Inspired by the strong learning ability from data, the neural network (NN) structure has been widely used in nonlinear function fitting [7]. The abstract features learned from neural networks together with the strengths of nonlinear approximations can process multiple types of data recovery problems in computer vision (CV) [8] and nature language processing (NLP) [9]. Moreover, neural networks have already been extended to communication systems including modulation recognition [11], channel estimation [12], channel decoding [13] and CSI feedback [14]. Generally, the communication system is considered as a black box with an end-to-end deep learning architecture [15], and all functionalities are embedded in several layers where the performance can be enhanced jointly. Similar with the training regimes in supervised learning, after back propagation and updates of parameters, the NN implementations learn efficient representations of data and achieve excellent performance.

Taken into consideration those work, in this paper, we present a deep learning based framework in SSK system. The contributions of this paper can be summarized as follows:

1. By characterizing the transmitter and receiver into an auto-encoder (AE), we design a novel end-to-end framework of SSK system. The implementations can be jointly optimized and finally we obtain convincing results competitive with current state-of-art ML methods.
2. We evaluate the adaptability of our proposed framework and verify the robustness with practical noise interferences. The system under consideration is composed of a rayleigh fading channel with white noise while suffering from a high power radar pulse interferences simultaneously. Our DL-based SSK framework can be applied directly and achieve reliable results.

The remainder of the paper is organized as follows. Section 2 describes our DL-based SSK model, including a brief introduction of SSK system. In Sect. 3, the simulation results are provided. The adaptability will be analyzed as well. Finally Sect. 4 concludes the paper.

2 System Model

2.1 SSK System

The SSK system model is composed of N_t transmit antennas and N_r receive antennas. A sequence of independent bit streams $\mathbf{b} = \{b_1, b_2, \cdots, b_k\}$ enters a channel encoder and the corresponding output $\mathbf{c} = \{c_1, c_2, \cdots, c_n\}$ is generated, where k and n represent the input and output dimensions of channel encoder, respectively. The sequence $\mathbf{c}$ then be modulated as the constellation point $\mathbf{x} = [x_1, x_2, \cdots, x_{N_\mathrm{t}}]^T$, where $\mathbf{x}$ corresponds to transmission information of $m = \log_2(N_\mathrm{t})$ bits. The power limit can thus be represented as

$$\mathbb{E}_x(\mathbf{x}^H\mathbf{x}) = 1. \tag{1}$$

Hence, the received signal is

$$\mathbf{y} = \sqrt{\rho}\mathbf{H}\mathbf{x} + \boldsymbol{\zeta}, \tag{2}$$

where $\mathbf{H}$ is an $N_\mathrm{r} \times N_\mathrm{t}$ wireless communication channel matrix, and is combined with an independent identically distributed (i.i.d) additive white Gaussian noise (AWGN) denoted as $\boldsymbol{\zeta} = [\zeta_1, \zeta_2, \cdots, \zeta_{N_\mathrm{r}}]^T$. ρ is the average signal to noise ratio (SNR) at each receive antenna. $\mathbf{H}$ and $\boldsymbol{\zeta}$ are subject to i.i.d complex Gaussian distribution, respectively.

Futhermore, SSK maps a set of m-bit information to symbol $\mathbf{x}_j$, which will then be transmitted through the j-th antenna. The symbol itself contains no information, while its position in the constellation point $\mathbf{x}$ indeed reflects the actual message. The one-hot vector $\mathbf{x}$ determines the index of the activated antenna which is thus defined as

$$\mathbf{x}_j \doteq [0, 0, \cdots, 1, \cdots, 0, 0]^T, \tag{3}$$

where 1 (the pulse) is the j-th element. The simplified received signal in Eq. 2 can be formulated as

$$\mathbf{y} = \sqrt{\rho}\mathbf{h}_j + \zeta, \tag{4}$$

in which $\mathbf{h}_j$ refers to the j-th column vector of channel transmission matrix $\mathbf{H}$. According to the prior that the probability of the signal input is equal, we adopt the optimal ML detector as

$$\hat{j} = \arg\max_j P_\mathbf{Y}(\mathbf{y} \mid \mathbf{x}_j, \mathbf{H}) = \arg\max_j \|\mathbf{y} - \sqrt{\rho}\mathbf{h}_j\|_F^2, \tag{5}$$

$$P_\mathbf{Y}(\mathbf{y} \mid \mathbf{x}_j, \mathbf{H}) = \frac{\exp(-\|\mathbf{y} - \sqrt{\rho}\mathbf{h}_j\|_F^2)}{\pi^{N_\mathrm{r}}}, \tag{6}$$

where $\|\cdot\|_F$ refers to the Frobenius norm of vectors and $\hat{j}$ is the discriminated index of the activated antenna.

In practical communication scenarios, where a distant noise with high power appears occasionally with a certain probability and contaminates the original transmitted signal, the overall channel noise deviates from Gaussian distribution and exhibits non-Gaussian characteristics. In this paper, we consider the interference of radar signals, which has caused widespread concern in the next generation of wireless communication system [11]. The transmitted signal can then be mathematically expressed as

$$\mathbf{y} = \sqrt{\rho}\mathbf{h}_j + \boldsymbol{\zeta} + \boldsymbol{\omega}, \tag{7}$$

where $\boldsymbol{\zeta}$ remains to be AWGN and $\boldsymbol{\omega}$ is the subject to the Gaussian distribution $\mathcal{N}(0, \sigma_\omega^2)$ with the probability of occurrence w:

$$\boldsymbol{\omega} \sim \begin{cases} \mathcal{N}(0, \sigma_\omega^2) & w \\ 0 & 1 - w \end{cases}. \tag{8}$$

Notice that σ_ω^2 is supposed to be a higher variance compared to AWGN.

2.2 Deep Learning-Based Model

Based on the above introduction, here we consider the deep learning-based SSK system in which the number of transmit antenna $N_\mathrm{t} = 4$ and the number of receive antenna $N_\mathrm{r} = 1$. To prevent confusion we denote the DL-based model as SSK-NN in the following sections. In conventional system, the activated antenna transmits a pulse and the entire information is conveyed through the antenna index. For our SSK-NN model, the activated antenna transmits a learned modulation constellation instead. The overall pipeline is represented in Fig. 1.

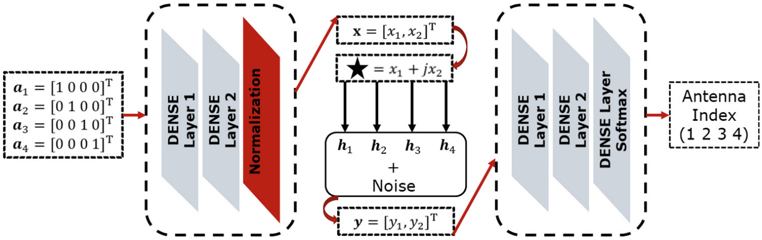

Fig. 1. The SSK-NN overall pipeline. The transmitter end adopts $\mathbf{a}_i$ as the input vector and the training samples for the neural network. In the receiver end, the received signal $\mathbf{y}$ will then be discriminated through two full-connected layers and finally classified by a softmax function.

The transmitter end adopts $\mathbf{a}_i$ as the input vector and the training samples for the neural network. The dimension of $\mathbf{a}$ equals to the number of transmit antenna $N_\mathrm{t} = 4$. Since each transmission activates only one antenna, $\mathbf{a}$ is associated with corresponding one-hot vector. The modulation unit is constructed with a three-layers AE where two fully-connected layers and one normalization layer can generate a two-dimension output $\mathbf{x}$. The normalization layer ensures the output constellation points satisfying the power limit and thus to meet the design requirements of communication physical layer. We then treat the two components of $\mathbf{x}$ as two values of I/Q paths and convert $\mathbf{x}$ to a constellation point. Therefore, immediately after the AE modulating a one-hot vector to the corresponding symbol, the activated antenna will transmit it through its own transmission path. Moreover, in the receiver end, the received signal $\mathbf{y}$ will then be discriminated through two full-connected layers and finally classified by a softmax function:

$$S_i = \frac{\exp(V_i)}{\sum_j \exp(V_j)}, \tag{9}$$

where V_i represents the output of the i-th neurons in the former layer. The cross-entropy loss will be calculated as

$$\text{Loss} = -\sum_{i=1}^{N_\text{t}} S_i \ln(S_i), \tag{10}$$

which then guides the back propagation and stochastic gradient descent (SGD) methods to update parameters in dense layers. Once the training process is completed, the obtained class number (the largest S_i) can predict the antenna index.

Specifically, our SSK-NN system has no strict requirement on the number of N_r in practical design. For simulation convenience, we choose $N_\text{r} = 1$ in this paper. Since the training process only makes use of $\mathbf{a}$ and $\mathbf{y}$, the NN architecture remains valid even though there is no channel analytic formula given. Overall, the communication system is considered as a black box with an end-to-end deep learning architecture and the parameters of NNs can be jointly optimized.

3 Simulation Results

In this section, we provide several simulation results to confirm the performance of our proposed model. The NN architecture is constructed through the system model. The parameters of the network structure are provided in Table 1.

Table 1. Network structure

Layers	Output dimensions
Dense+ReLu	4
Dense	2
Normalization	2
·Channel+Noise	2
Dense+ReLu	2
Dense+ReLu	2
Dense+Softmax	4

To meet the power limit, the noise layer is represented with a definite variance $\sigma = (2RE_b/N_0)^{-1}$, where E_b/N_0 refers to the ratio of energy per bit E_b and noise power spectral density N_0. The communication rate of the system is $R = 1$ and the fixed energy constraint is $\|\mathbf{x}\|_2^2 = 2$ (the dimension of the output constellation). We measure the SSK-NN performance using block error rate (BLER), i.e. $P(\hat{j} \neq j)$ and compare the trained neural networks with ML detection methods. Without loss of generality, the training set consists of 1000 samples and is trained for 150 epoches. The code is implemented in PyTorch.

3.1 The Baseline Model

Based on Fig. 1, the transmitter consists of a three-layers feed forward NN, the channel is represented by an fixed-variance additive noise layer and the receiver is implemented as a feed forward NN as well. The AE is trained end-to-end using Adam [16] on the set of all possible messages, i.e. four kinds of **a**. The cross-entropy loss function is used and the learning rate is set as 0.001. Training is completed at a fixed value $E_b/N_0 = 7\,\text{dB}$ and testing is done at the SNR ranging from $-2\,\text{dB}$ to $10\,\text{dB}$. The BLER comparison is provided in Fig. 2. Notice that in AWGN channels, the ML detection is optimal theoretically. The similar performance provided above indeed verifies the feasibility of our deep learning method.

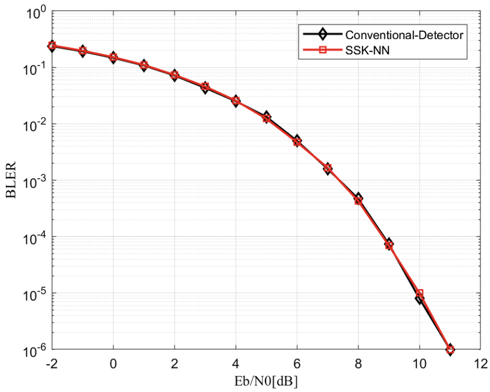

Fig. 2. $N_\text{t} = 4$ and $N_\text{r} = 1$. Trained at SNR = 7 dB.

3.2 The Transmission Model

Considering the time-invariant channel following a standard complex Gaussian distribution $\mathcal{CN}(0, 1)$. The power limit of $\mathbf{y}$ will still be satisfied owing to the fixed unit variance. In addition, the AWGN still exists. The considered channel is represented by a multiplier matrix $\mathbf{H}$ combined with the additive layer. The AE is trained end-to-end using Adam optimizer at a fixed SNR = 7 dB and a learning rate 0.001 as well. The BLER comparison is presented in Fig. 3. Specifically, there is a consistent performance gain in a wide testing SNR range, from $-2\,\text{dB}$ to $10\,\text{dB}$. Our SSK-NN optimizes the AE with respect to the transmission channel and outperforms the ML detection, getting benefit from the adaptive constellation design.

In practical communications, the training process needs to be conducted first. Then the desirable demodulation performance can be obtained over the entire range of noises just after a quick parameter fine-tuning adjustment. For a more convincing comparison, the constellation needs to be examined with some higher-order modulation schemes, applying a channel code for instance. Discussion of these topics is out of the scope of this paper and left to our further research.

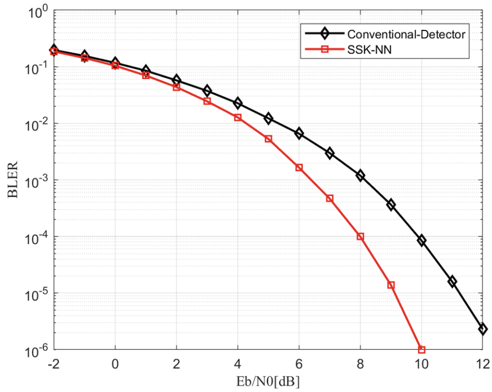

Fig. 3. $N_\mathrm{t} = 4$ and $N_\mathrm{r} = 1$. Complex Gaussian channels are considered. Trained at SNR = 7 dB.

3.3 Adaptability in Interfering Channels

Since the training process regards the channel as a black-box, only the signal input $\mathbf{x}$ and the received symbol $\mathbf{y}$ are concerned, which suggests the experiments on non-Gaussian channels worthy a try. We recall the radar interferences introduced in Sect. 2. The non-Gaussian channel model we focus here can be mathematically represented as Eq. 7. Following the above channel design approach, the expression of non-Gaussian radar interferences noise is consistent with the AWGN. The additional noise layer with the fixed variance σ_ω^2 will be added to the NN structure. The training SNR of AWGN is set to be 7 dB while the SNR of radar interferences is 5 dB of higher power. The possibility of interferences occurrence is 0.01, which implies the sporadic and unpredictable of such non-Gaussian scenarios. We still adopt the Adam optimizer with learning rate 0.001 and the BLER results are shown in Fig. 4. Considering the NN implementation and the traditional ML scheme of non-Gaussian noise in the case of 5 dB, both of them have some degradation with respect to the ideal channel setting. Obviously, the SSK-NN outperforms ML at the whole SNR testing ratio. The neural network utilizes its ability to simulate nonlinear degradation and achieve the optimization for communication under non-Gaussian channels.

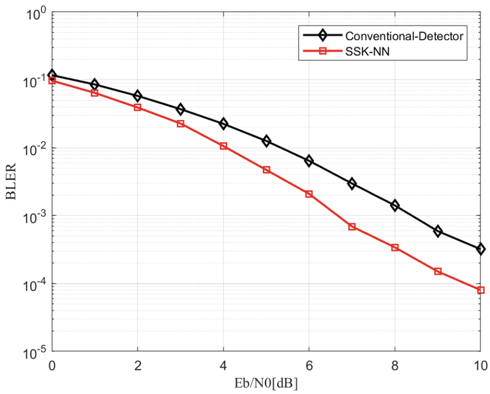

Fig. 4. $N_t = 4$ and $N_r = 1$. Complex Gaussian channels are considered. Trained at SNR = 7 dB with 5 dB radar noises.

4 Conclusion

In this paper, we propose an ene-to-end neural network implementation of SSK system. We develope an AE to design proper constellation points and the corresponding demodulation scheme is obtained simultaneously. The advantages in simulating non-linear functions of deep learning method is taken to overcome the non-Gaussian interference in communication scenarios. The results are analyzed and the comparison convinces that our model presents competitive performance with strong adaptability under non-Gaussian interference.

The lightweight network constructed in SSK system can be expanded to more complicated communication scenarios with more sophisticated network structure. We will continue to investigate for further applications.

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