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A Learning Approach for Optimal Codebook Selection in Spatial Modulation Systems

In spatial modulation (SM) systems that utilize multiple transmit antennas/patterns with a single radio front-end, we propose a learning approach to predict the average symbol error rate (SER) conditioned on the instantaneous channel state. We show that the predicted SER can be used to lower the average SER over Rayleigh fading channels by selecting the optimal codebook in each transmission instance. Further by exploiting that feedforward artificial neural networks (ANNs) trained with a mean squared error (MSE) criterion estimate the conditional a posteriori probabilities, we maximize the expected rate for each transmission instance and thereby improve the link spectral efficiency.

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1 Introduction

Multi-antenna wireless communication systems provide significant capacity gains by exploiting the available spatial degrees of freedom in rich scattering environments. Spatial modulation (SM) [1], where information is encoded onto the choice of transmitting antenna in addition to the transmitted symbols, provides a practical means for multi-antenna gains in transmitters constrained by a single radio front-end, e.g., low-complexity devices in an Internet of Things (IoT) framework. However since the choice of transmitting antenna in SM depends on the information bit stream, it is difficult to predict the optimal transmission parameters in stochastic channels [2]. Recently, a SM codebook selection scheme that relies on full or quantized channel state fed back to the transmitter has been proposed [3], where a heuristic based approach is used to approximate the optimal SM codebook containing the (antenna, symbol) pairs. On the other hand, machine learning approaches where the receiver utilizes the channel estimate to select one out of a finite set of pre-defined codebooks based on k-nearest neighbor scheme have also been proposed [4, 5]. Although these schemes limit the feedback to few bits indicating the choice of codebook, they suffer from a high computational complexity unsuitable for real-time execution and do not provide an estimate of the codebook error probability. In this paper, we propose a deep learning approach that predicts the average symbol error probability for each codebook conditioned on the channel state, relying on the fact that sufficiently parameterized feedforward artificial neural networks (ANNs) are good Bayesian a posteriori estimators [6] and show that sufficiently trained ANNs lower the symbol error rate for single- as well as multi-antenna SM receivers. Further, we exploit the predicted symbol error probability to select the codebook that maximizes the expected rate in each transmission instance, and demonstrate that our approach improves the spectral efficiency of the link.

2 System Model

We assume N_t antennas at the transmitter and N_r antennas at the receiver in a frequency flat communication channel, and that the transmitter is equipped with a single radio front-end as shown in Fig. 2.1. The $N_r \times 1$ received signal is given by

$$\mathbf{y} = \sqrt{\rho}\alpha\mathbf{H}\mathbf{x}_i + \mathbf{w}, \quad (2.1)$$

where ρ is the average received signal-to-noise ratio (SNR), $\alpha \in \Omega_i$ is the transmitted symbol and i is the transmitting antenna, $\mathbf{H} = [\mathbf{h}_1, \dots, \mathbf{h}_P]$ is the $N_t \times N_r$ channel matrix, $\mathbf{x}_i = [\delta(i, 1), \dots, \delta(i, N_t)]^T$ is the antenna selection vector, and $\mathbf{w} \in \mathbb{C}^{N_r}$ the additive white Gaussian noise (AWGN) with variance σ^2 . The SM receiver estimates the (antenna, symbol) combination, $(\tilde{i}, \tilde{\alpha})$, that minimizes the Euclidean distance $\|\mathbf{y} - \tilde{\alpha}\tilde{\mathbf{H}}\mathbf{x}_{\tilde{i}}\|$. A successful symbol transmission occurs when $(\tilde{i}, \tilde{\alpha}) = (i, \alpha)$ and is denoted by $s = 1$. The problem of codebook selection is to

find the codebook $\mathcal{C} : \{\Omega_1, \dots, \Omega_{N_t}\}$ that satisfies the given optimality criteria often related to the symbol error rate (SER). In this paper, we restrict Ω_i to M -PSK symbols, where $M \in \{0, 2, 4, \dots\}$ and $M = 0$ implies that the antenna will not transmit.

Figure 2.1: SM based on the choice of one transmit antenna and one symbol from a codebook. The receiver estimates the optimal codebook based on the instantaneous channel state and feeds it back to the transmitter.

3 Conditional Probability Estimation Using Feedforward ANNs

ANNs are parameterized models for approximating non-linear mappings in a high-dimensional space. A fully connected L -layer feedforward ANN has the activation

$$\eta^{(l)} = \phi^{(l)} \left(\mathbf{W}^{(l)} \eta^{(l-1)} + \mathbf{b}^{(l)} \right) \quad (3.1)$$

at the l^{th} layer, where $\mathbf{W}$ and $\mathbf{b}$ are the trainable weight and bias parameters at the l^{th} hidden layer, $l \in \{1, \dots, L\}$, and ϕ is an element-wise nonlinear function. We denote the ANN parameters by θ and its output by $f(\gamma; \theta)$, where γ is the observed channel state. The optimal ANN parameters that minimize the MSE loss between the outputs and the observed binary success variable for several symbol transmissions using an arbitrary codebook are

$$\theta^{\text{opt}} = \arg \min_{\theta} \mathcal{L}(\theta) \quad (3.2)$$

$$= \arg \min_{\theta} \frac{1}{N} \sum_{n=1}^N (s_n - f(\gamma; \theta))^2 \quad (3.3)$$

$$\theta^{\text{opt}} \xrightarrow{N \rightarrow \infty} \arg \min_{\theta} E\{(s - f(\gamma; \theta))^2\}, \quad (3.4)$$

Figure 3.1: NN for estimation of the error probability induced by SNRs $\{\tilde{\gamma}_i\}$ for each mode transmission mode $m \in \{1, \dots, M\}$.

where the expectation is taken over $P_{S,\mathbf{r}}(s, \gamma)$. Following the general approach suggested in [6], we expand the expectation to obtain

$$\mathcal{L}(\theta) \approx \int \sum_{s \in \{0,1\}} (s - f(\gamma; \theta))^2 P_{S,\mathbf{r}}(s, \gamma) d\gamma \quad (3.5)$$

$$= \int \sum_{s' \in \{0,1\}} \sum_{s \in \{0,1\}} (s - f(\gamma; \theta))^2 P_{S|\mathbf{r}}(s|\gamma) P_{s',\mathbf{r}}(s', \gamma) d\gamma \quad (3.6)$$

$$= E \left\{ f^2(\gamma; \theta) - 2f(\gamma; \theta)E\{s|\gamma\} + E\{s^2|\gamma\} \right\} \quad (3.7)$$

$$= E \left\{ (f(\gamma; \theta) - E\{s|\gamma\})^2 \right\} + E \left\{ \text{var}\{s|\gamma\} \right\} \quad (3.8)$$

where we obtain Eq. 3.7 by noting that $f(\gamma; \theta)$ is independent of the channel. We observe from Eq. 3.8 that the loss is minimized when the ANN outputs estimate the conditional expectation of successful symbol transmission.

4 Optimal Codebook Selection

In this paper, we assume that there exist a finite set of available candidate codebooks, $\{\mathcal{C}_j\}_{j \in \{1, \dots, J\}}$, where the cardinality of each codebook $|\mathcal{C}_j|$ corresponds to a maximum spectral efficiency of $\log_2 |\mathcal{C}_j|$ bits/s/Hz. We utilize the ANN structure described in the previous section to predict the conditional expectation of symbol success for each candidate codebook, conditioned on the instantaneous channel state. When the optimality criterion is defined as minimizing the SER at a fixed rate (e.g., in low-latency applications), we select the codebook index with the maximum predicted conditional expectation of success,

$$\tilde{j} = \arg \max_j f_j(\gamma; \theta). \quad (4.1)$$

Further, when the optimality criterion is defined as maximizing the spectral efficiency of the link, we select the codebook index that maximized the expected

Table 5.1: Simulation Parameters

N_t	4
N_r	1 (Fig. 5.1), 4 (Fig. 5.2-5.3)
Channel fading	i.i.d $\mathcal{CN}(0, \mathbf{I}_8)$
Possible constellation sizes	$\{0, 2, 4, 8, 16, 32\}$
Bits per channel use	4

Table 5.2: Candidate Codebooks

Codebook Index	$[\Omega_0 , \Omega_1 , \Omega_2 , \Omega_3]$
0	[16, 0, 0, 0]
1	[8, 8, 0, 0]
2	[8, 4, 4, 0]
3	[8, 4, 2, 2]
4	[4, 4, 4, 4]

rate,

$$\tilde{j} = \arg \max_j f_j(\gamma; \boldsymbol{\theta}) \log_2 |\mathcal{C}_j|. \quad (4.2)$$

5 Results

The SM link parameters are provided in Table 5.1. We characterize the channel state by a vector containing the received SNR for each transmit-receive antenna pair, $\frac{\|h_{ij}\|^2}{\sigma^2}$. We assume perfect knowledge of the channel at the receiver, and assume that the correlation coefficient for transmit as well as receive antennas is $r = 0.9$.

The SERs for 4×1 and 4×4 SM link are shown in Fig. 5.1 and Fig. 5.2 respectively, where we observe that the ANN lowers the SER in both cases compared to a fixed codebook selection. Candidate codebooks for this simulation are given in Table 5.2, which have a fixed cardinality $|\mathcal{C}_j| = 16$. In fig. 5.2, we assume that the channel between each transmit and receive antenna suffers from i.i.d. Rayleigh fading and a deterministic antenna correlation $|r^{i'-j'}|$, where $i', j' \in [N_t]$ and $i', j' \in [N_r]$ at the transmitter and the receiver respectively.

In Fig. 5.3, we plot the achieved rates for fixed codebooks as well as ANN based codebook selection. The space of candidate codebooks in this case are codebooks with cardinalities $|\mathcal{C}_j| \in \{2, 4, 8, 16, 32, 64\}$. The codebooks with smaller cardinalities achieve a lower symbol error rate while codebooks with a higher cardinalities provide a higher maximum spectral efficiency. We observe that the ANN based approach is able to exploit these complementary gains by predicting the expected rate for each codebook at each transmission instance, resulting in significant spectral efficiency gains over fixed codebooks.

Figure 5.1: SER for SM over 4×1 channel, with the codebooks defined in Table 5.2. The ANN approach predicts the optimal codebook in each transmission instance to provide up to 4 dB gain in the average SER.

Figure 5.2: SER for SM over 4×4 channel, $r = 0.9$ with the codebooks defined in Table 5.2. The ANN approach predicts the optimal codebook in each transmission instance to provide up to 2 dB gain in the average SER.

Figure 5.3: Spectral efficiency for $N_t \times N_r = \{4 \times 4\}$, $r = 0.9$ with ANN (black, solid) based rate selection that maximizes the expected rate for each transmission. The “Fixed Codebook” curves (multiple colors, dashed) are obtained by fixing the codebook over the entire test dataset.

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