A DNN Architecture for the Detection of Generalized Spatial Modulation Signals

Bharath Shamasundar and A. Chockalingam
Department of ECE, Indian Institute of Science, Bangalore 560012

Abstract—In this paper, we consider the problem of signal detection in generalized spatial modulation (GSM) and explore the utility of the deep neural networks (DNN) for the detection task. We propose a DNN architecture which uses small sub-DNNs to detect the active antennas and the constellation symbols transmitted by the active antennas. Under the assumption of i.i.d. additive white Gaussian noise (AWGN), the proposed DNN detector achieves a performance very close to that of maximum likelihood detector. We also analyze the performance of the proposed detector under two conditions of practical interest: i) correlated noise across receive antennas (resulting from mutual coupling, matching networks) and ii) noise distribution deviating from the standard AWGN model. The proposed DNN-based detector learns the deviations from the standard model and achieves superior performance compared to that of conventional maximum likelihood detector.

Keywords – Deep neural networks, generalized spatial modulation, signal detection, correlated noise, non-Gaussian noise.

I. INTRODUCTION

Index modulation techniques are attracting increased research attention due to their ability to achieve high throughput and superior bit error performance at lesser hardware complexity [1],[2]. Spatial modulation (SM) [3] is a popular example of index modulation which uses \( n_t \) transmit antennas and a single transmit radio frequency (RF) chain. In a given channel use, one of the transmit antennas is selected based on \( \log_2 n_t \) information bits and a symbol from a conventional modulation alphabet \( \mathcal{A} \) (QAM/PSK) is transmitted on the selected antenna. Thus SM achieves a rate of \( \log_2 n_t + \log_2 |\mathcal{A}| \) bits per channel use (bpcu). SM has the advantages of eliminating multi-antenna interference and low RF hardware complexity.

A drawback with SM is that its reduced hardware complexity comes at the cost of the reduced throughput. This drawback is overcome by the generalized SM (GSM), which allows multiple transmit antennas to be active simultaneously [4]. GSM system uses \( n_t \) transmit antennas and \( n_{rf} \) RF chains, \( 1 < n_{rf} < n_t \). In each channel use, \( n_{rf} \) out of the \( n_t \) transmit antennas are selected based on \( \log_2 n_{rf}^{(n_t)} \) information bits and \( n_{rf} \) symbols from the modulation alphabet \( \mathcal{A} \) are transmitted from the selected active antennas. The achieved rate in GSM is therefore \( \log_2 n_{rf}^{(n_t)} + n_{rf} \log_2 |\mathcal{A}| \) bpcu. It has been shown in [4] that, with suitable \((n_t, n_{rf})\) combination, a GSM system can achieve both high throughput and superior bit error performance compared to the spatial multiplexing system which uses all its transmit antennas to convey symbols from the modulation alphabet. In the present work, we consider the problem of signal detection for GSM and explore the utility of deep neural networks (DNN) for the detection task.

Deep learning (DL) has revolutionized many areas including computer vision, natural language processing, and speech recognition. It is also being successfully applied in several other fields such as biology, finance, and social behavior analysis. Recently, DL has been applied in wireless communications for designing intelligent communication systems [5]-[9]. Specifically, in the physical layer, DL has been applied in two important ways: i) as a replacement to the existing communication blocks like channel coding [9] and signal detection [10] blocks, and ii) for designing end-to-end communication systems without traditional communication blocks [3]. Both the approaches have shown promising results by outperforming the existing classical techniques. Taking the line of DNN approach, in this paper, we consider the problem of GSM signal detection using DNNs and show interesting results. Our contributions in the present work can be summarized as follows.

- We propose a novel DNN architecture which uses smaller sub-DNNs for the detection of the indices of the active antennas and the transmitted modulation symbols in GSM, and report the following interesting results on the performance of the proposed DNN-based detection.
- When the thermal noise across different receive antennas are i.i.d additive white Gaussian (AWGN), the proposed DNN architecture is shown to achieve a detection performance which is very close to that of the optimum maximum likelihood detection.
- When the thermal noise across different receive antennas are correlated, which arises in practice due to mutual coupling among the receive antennas, matching networks, etc., the DNN-based detector achieves an excellent performance by learning the noise correlation. Also, when the noise is i.i.d but the distribution slightly deviates from Gaussian, the proposed DNN architecture learns a good detector for the non-Gaussian noise distribution, achieving better performance compared to that of the conventional maximum likelihood detector. It is noted that in both these cases of correlated noise and non-Gaussian noise, conventional maximum likelihood detection results in degraded performance.

The rest of the paper is organized as follows. In Sec. [II] we introduce the GSM system model. In Sec. [III] we present the proposed DNN architecture for GSM signal detection. Results and discussions are presented in Sec. [IV] Conclusions are presented is Sec. [V].

II. GSM SYSTEM MODEL

Consider a multiple-input multiple-output (MIMO) communication system with \( n_t \) transmit antennas and \( n_r \) receive antennas. Let \( n_{rf} \), \( 1 < n_{rf} < n_t \), denote the number of transmit
RF chains at the transmitter. In GSM, in a channel use, \( n_{rf} \) out of the \( n_t \) transmit antennas are selected based on \[ \log_2 \left( \frac{n_t}{n_{rf}} \right) \] information bits. The selected \( n_{rf} \) antennas are called active antennas, on which \( n_{rf} \) symbols from a modulation alphabet \( \mathbb{A} \) (say, QAM) are transmitted based on \( n_{rf} \log_2 |\mathbb{A}| \) information bits. The remaining \( n_t - n_{rf} \) antennas are silent. An \( n_{rf} \times n_t \) switch connects the RF chains to the antennas to be activated.

The achieved rate in GSM is given by

\[
\eta = \left[ \log_2 \left( \frac{n_t}{n_{rf}} \right) \right] + n_{rf} \log_2 |\mathbb{A}| \quad \text{bpcu. (1)}
\]

Let \( \mathbb{A}_0 = \mathbb{A} \cup 0 \). The GSM signal set is a set of \( n_t \)-length GSM signal vectors given by

\[
\mathbb{S} = \{ \mathbf{x} | \mathbf{x} \in \mathbb{A}_0, ||\mathbf{x}||_0 = n_{rf}, \mathbf{t}^x \in \mathbb{T}_\mathbb{A} \},
\]

where \( ||\mathbf{x}||_0 \) denotes the \( l_0 \)-norm of \( \mathbf{x} \) (the number of non-zero elements in \( \mathbf{x} \) ), \( \mathbf{t}^x \) is the antenna activation pattern (AAP) for the GSM signal vector \( \mathbf{x} \) which is an \( n_t \)-length binary vector with \( t_i^x = 1 \) if \( x_i \in \mathbb{A} \) and ‘0’ otherwise, where \( t_i^x \) and \( x_i \) are \( i \) th elements of \( \mathbf{t}^x \) and \( \mathbf{x} \), respectively, and \( \mathbb{T}_\mathbb{A} \) is the set of all valid AAPs. Denoting \( \mathbf{H} \) to be the \( n_r \times n_t \) MIMO channel matrix, the \( n_r \times 1 \) received signal vector \( \mathbf{y} \) is given by

\[
\mathbf{y} = \mathbf{Hx} + \mathbf{n}, \quad \text{(3)}
\]

where \( \mathbf{x} \in \mathbb{S} \) and \( \mathbf{n} \) is an \( n_r \times 1 \) noise vector. Assuming perfect channel knowledge at the receiver, the maximum likelihood (ML) detection rule for GSM signal detection is given by

\[
\hat{s} = \arg\min_{\mathbf{x} \in \mathbb{S}} ||\mathbf{y} - \mathbf{Hx}||^2. \quad \text{(4)}
\]

The ML detection rule requires searching over all possible GSM transmit vectors and hence the complexity grows exponentially with the number of transmit antennas. Further, it is important to note that the ML detection rule in (4) is optimal only when the noise samples across the receive antennas are i.i.d and follow Gaussian distribution. Any deviation in noise from this standard model will result in suboptimal performance when the ML detection in (4) is used. This key observation motivates the use of techniques based on learning to alleviate the suboptimal performance when there is deviation from the standard model. Accordingly, in the following sections, we propose a DNN architecture for GSM signal detection and assess its performance.

III. DNN-BASED GSM DETECTOR

It is noted that GSM signal detection involves i) detecting the set of \( n_{rf} \) active antennas and ii) detecting \( n_{rf} \) constellation symbols \( s_1, s_2, \ldots, s_{n_{rf}} \in \mathbb{A} \) transmitted from the active antennas. To do this, we propose the DNN architecture shown in Fig. 1. The proposed DNN in Fig. 1 comprises of \( n_{rf} + 1 \) smaller sub-DNNs. One sub-DNN is used to detect the indices of the \( n_{rf} \) active antennas (which is shown as AAP-DNN, where AAP refers to antenna activity pattern) and \( n_{rf} \) sub-DNNs are used for detecting \( n_{rf} \) modulation symbols transmitted from the active antennas (which are shown as Sym-1 DNN, · · · , Sym-\( n_{rf} \) DNN). All the sub-DNNs have \( 2n_r \) input neurons through which the real and imaginary parts of the received signal vector are fed as inputs.

**AAP-DNN:** The AAP-DNN has a set of hidden layers (where the number of hidden layers is a tunable parameter) and an output layer with \( n_t \) neurons. Each neuron in the output layer corresponds to one transmit antenna and gives the probability of that antenna being active. We use sigmoid activation in the output layer so that the probabilities are independent across the output neurons and need not sum to one. This enables the output layer to indicate multiple active antennas by giving high probability values corresponding to the active antennas. The ‘\( n_{rf} \) max. indices selector’ takes the \( n_t \) probability values from the output neurons as input and declares the \( n_{rf} \) antennas corresponding to the \( n_{rf} \) highest probability values to be active.

**Symbol-DNN:** Each of the Sym-\( i \), \( i = 1, \ldots, n_{rf} \) DNNs has a set of hidden layers and \( M = |\mathbb{A}| \) output neurons. Each output neuron of the Sym-\( i \) DNN corresponds to one symbol of \( \mathbb{A} \) and gives the probability of that symbol being sent from the \( i \) th antenna. Softmax activation is used for the output neurons of the symbol-DNNs. Hence, the probabilities in a given symbol-DNN are dependent across the output neurons and they sum to one. That is, only one of the \( M \) neurons in each symbol-DNN will result in a high probability value, which will be declared as the transmitted symbol by the ‘max. index selector’ followed by the ‘index to symbol mapper’ blocks.

A static/slowly varying channel with a long coherence-time is assumed so that the detector can be trained initially with \( m_T \) labeled training examples and then subsequently be used for signal detection. In the training phase, the transmitter sends \( m_T \) pseudo-random GSM signal vectors. The received signal vectors are used as inputs to train the AAP-DNN and symbol-DNNs. After the training phase, GSM signal vectors selected by the random information bits are transmitted in the testing phase and are detected using the trained DNN. We use the tensorflow and keras framework for training and testing the proposed DNN architecture. More details on the parameters used in the DNN architecture will be provided in the next section.
IV. RESULTS AND DISCUSSIONS

In this section, we present the bit error rate (BER) performance of GSM with the proposed DNN-based detection under different assumptions on the noise statistics.

A. BER with i.i.d Gaussian noise

In this subsection, we present the BER performance when the noise samples across the receive antennas are i.i.d and complex Gaussian with mean zero and variance $\sigma^2$. Figure 2 shows the BER performance of GSM using the proposed DNN-based detector. The considered GSM system uses $n_t = n_r = 4$, $n_{rf} = 2$, and BPSK modulation. The BER performance with maximum likelihood detector and linear minimum mean square error (MMSE) detector are also shown for comparison. The considered DNN architecture has three sub-DNNs for this system setting, one sub-DNN for detecting the two active antennas and the other two sub-DNNs for detecting the two BPSK symbols transmitted by the active antennas. The DNN parameters used for the system configuration in Fig. 2 are presented in Table I.

| Parameters               | APP-DNN | Symbol-DNN |
|--------------------------|---------|------------|
| No. of input neurons     | $2n_t = 8$ | $2n_r = 8$ |
| No. of input neurons     | $n_t = 4$ | $|A| = 2$ |
| No. of hidden layers     | 5       | 3          |
| Hidden layer activation   | ReLU    | ReLU       |
| Output layer activation   | Sigmoid | Softmax    |
| Optimizer                | Adam    | Adam       |
| # No. of training examples| 10,000  | 10,000     |
| Training SNR             | 10 dB   | 10 dB      |
| No. of epochs            | 20      | 20         |

TABLE I: DNN parameters of the proposed detector in Fig. 2

From Table I it can be seen that both APP-DNN and Symbol-DNNs have $2n_r = 8$ input neurons through which the received signal is fed to the hidden layers. Both APP-DNN and Symbol-DNNs use three fully connected (FC) hidden layers and use rectified linear unit (ReLU) activation. The APP-DNN has $n_t = 4$ output neurons and sigmoid activation is used for the output layer. The symbol-DNNs have $|A| = 2$ output neurons and softmax activation is used for the output layer. The following architectures are used for APP-DNN and Symbol-DNNs.

**APP-DNN:**

\[ i/p \rightarrow 16 \rightarrow \text{ReLU} \rightarrow 16 \rightarrow \text{ReLU} \rightarrow 8 \rightarrow \text{ReLU} \rightarrow 4 \rightarrow \text{sigmoid}. \]

**Symbol-DNN:**

\[ i/p \rightarrow 16 \rightarrow \text{ReLU} \rightarrow 16 \rightarrow \text{ReLU} \rightarrow 8 \rightarrow \text{ReLU} \rightarrow 2 \rightarrow \text{softmax}. \]

In the above architectures, numbers denote the number of neurons in a given layer, which is followed by the activation function used in that layer. For example, the APP-DNN uses 16 neurons in the first hidden layer with ReLU activation, followed by another 16 neurons in the second hidden layer with ReLU activation, followed by 8 neurons in the third hidden layer with ReLU activation, and finally 4 output neurons with sigmoid activation function. The DNN is trained at a single SNR value of 10 dB. The channel is considered to be static with the channel gains taking values from an instance of Rayleigh flat fading channel. From Fig. 2 it can be seen that the performance of the considered GSM system with the proposed DNN architecture is very close to that with the ML detector and is much superior to that with linear MMSE detector. It should be noted that the sizes of the sub-DNNs considered here are very small compared to the sizes of DNNs considered in the recent architectures in areas like computer vision. The proposed architecture is hence practically implementable on limited hardware resources.

We next consider large-scale GSM systems which use higher number of transmit and receive antennas. As in Fig. 2 we assume the noise to be i.i.d across the receive antennas and distributed $CN(0, \sigma^2)$. Figure 3 shows the BER performance of two large-scale GSM systems (System-1 and System-2) using the proposed DNN-based detection. MMSE detection performance is also shown for comparison. The DNN parameters used for detection in the two GSM systems considered in Fig. 3 are shown in Tables II and III respectively. The following architectures are used for APP-DNN and Symbol-DNNs for the two systems.

**APP-DNN:**

\[ i/p \rightarrow 128 \rightarrow \text{ReLU} \rightarrow 64 \rightarrow \text{ReLU} \rightarrow 32 \rightarrow \text{ReLU} \rightarrow 16 \rightarrow \text{ReLU} \rightarrow 8 \rightarrow \text{sigmoid}. \]

**Symbol-DNN:**

\[ i/p \rightarrow 32 \rightarrow \text{ReLU} \rightarrow 16 \rightarrow \text{ReLU} \rightarrow 8 \rightarrow \text{ReLU} \rightarrow 4 \rightarrow \text{ReLU} \rightarrow 2 \rightarrow \text{softmax}. \]

All the layers in the above architectures for System-1 and System-2 are FC and are systematic in the sense that the number of neurons gradually decrease from the first hidden layer to the output layer. It can be seen from Fig. 3 that the GSM systems using the proposed DNN architecture achieve significantly better BER performance compared to the linear MMSE detector, thus demonstrating the suitability and scalability of the proposed detector for large-scale GSM systems.

B. BER with correlated thermal noise

We now consider the performance of GSM when the thermal noise is correlated across different receive antennas. This arises in practice due to mutual coupling among closely spaced
TABLE II: DNN parameters of the proposed detector for System-1 in Fig. 3

| Parameters                  | AAP-DNN | Symbol-DNN |
|-----------------------------|---------|------------|
| No. of input neurons        | 2n_r = 16 | 2n_r = 16 |
| No. of output neurons       | n_t = 8  | [A] = 2    |
| No. of hidden layers        | 4        | 4          |
| Hidden layer activation     | ReLU     | ReLU       |
| Output layer activation     | Sigmoid  | Softmax    |
| Optimizer                   | Adam     | Adam       |
| No. of training examples    | 50,000   | 50,000     |
| Training SNR                | 10 dB    | 10 dB      |
| No. of epochs               | 50       | 50         |

TABLE III: DNN Parameters of the proposed detector for System-2 in Fig. 3

| Parameters                  | AAP-DNN | Symbol-DNN |
|-----------------------------|---------|------------|
| No. of input neurons        | 2n_r = 20 | 2n_r = 20 |
| No. of output neurons       | n_t = 10 | [A] = 4  |
| No. of hidden layers        | 5        | 5          |
| Hidden layer activation     | ReLU     | ReLU       |
| Output layer activation     | Sigmoid  | Softmax    |
| Optimizer                   | Adam     | Adam       |
| No. of training examples    | 50,000   | 50,000     |
| Training SNR                | 14 dB    | 14 dB      |
| No. of epochs               | 100      | 100        |

receive antennas, matching networks, etc. [11], [12]. A thermal noise correlation matrix that characterizes this correlation in multi-antenna systems has been derived in [11] by using Nyquist’s thermal noise theorem. This model depends on the receiver hardware parameters, and hence is not a general model for different hardware implementations. The lack of such a general model for the receiver noise correlation makes it infeasible to analytically derive the corresponding optimal detector. DNNs become much relevant in this context as they can learn to map the received signal to the transmitted signal by learning the underlying model including the noise correlation specific to the receiver hardware. Accordingly, we employ the DNN-based detector proposed in Sec. II for GSM signal detection in the presence of correlated noise. For the purpose of illustration, we consider a correlation model where the thermal noise correlation matrix \( N_c \) is of the form

\[
N_c = \begin{bmatrix}
1 & \rho_n & \rho_n^2 & \ldots & \rho_n^{n_r-1} \\
\rho_n & 1 & \rho_n & \ldots & \rho_n^{n_r-2} \\
\vdots & & & & \ddots \\
\rho_n^{n_r-1} & \rho_n^{n_r-2} & \ldots & 1
\end{bmatrix},
\]

where \( \rho_n (0 \leq \rho_n \leq 1) \) is the correlation coefficient. With this, the correlated noise across the receive antennas is \( \mathbf{n}_c = N_c \mathbf{n} \), where \( \mathbf{n} \) is the i.i.d AWGN noise vector with its entries from \( \mathcal{CN}(0, \sigma^2) \).

Figure 3 shows the BER performance of GSM in the presence of correlated thermal noise when the proposed DNN-based detector is used. The GSM system and DNN architecture parameters considered are the same as those considered in Fig. 2. The performance is shown for two \( \rho_n \) values, viz., 0.4 and 0.6. The performance with the ML detector in (4) with correlated noise is also shown. Note that (4) is optimum only when noise is i.i.d. Gaussian. Accordingly, the BER performance of ML detection in (4) with i.i.d AWGN noise is also shown in the figure for comparison.

The following observations can be made from Fig. 4. First, it can be seen that the performance of GSM using the ML detector in (4) in the presence of correlated noise degrades compared to the case with i.i.d AWGN. This is expected because the ML detector in (4) is optimal when the noise across the receive antennas are i.i.d AWGN, and using this detector in correlated noise leads to suboptimal detection. Whereas, the performance with the proposed DNN-based detector is better than that with the ML detector for both the \( \rho_n \) values. In fact, the performance of the proposed detector with correlated noise is better than that of ML detection with i.i.d AWGN. These interesting observations can be explained as follows. Among all the noise sequences of equal average energy, i.i.d Gaussian noise (uncorrelated thermal noise) is the the worst case noise as it has the maximum entropy [13], [14]. The correlation introduces a structure in the noise which allows the DNN to effectively learn the model and thus achieve superior performance compared to the case of uncorrelated noise.
Fig. 5: Probability density functions of standard normal distribution and $t$-distribution with $\nu = 10$ and $\nu = 5$.

thermal noise. For example, it can be seen that, at a BER of $10^{-3}$ and $\rho_n = 0.6$, the performance of GSM with the proposed detector is about 4 dB superior compared to that with the ML detector. It is also better than the ML detection performance in i.i.d AWGN by about 3 dB.

C. BER with non-Gaussian noise

We next consider the case when the noise samples across different receive antennas are i.i.d, but deviate from Gaussian distribution. Specifically, we consider the case when the noise samples have $t$-distribution, parameterized by parameter $\nu$. The probability density functions of the standard normal distribution and $t$-distribution (with $\nu = 10$ and 5) are shown in Fig. 5. It can be seen that the distributions look very similar with $t$-distribution deviating slightly from standard Gaussian, such that smaller the value of $\nu$ more is deviation from standard Gaussian.

Figure 6 shows the BER performance of GSM using the proposed DNN-based detector when the noise samples are i.i.d across the receive antennas and follow $t$-distribution with $\nu = 10$ and $\nu = 5$. The considered GSM system and the DNN architecture are same as those considered in Fig. 2. The performance with ML detection in (4) under i.i.d $t$-distributed noise as well as i.i.d Gaussian noise are also shown for comparison. From Fig. 6, it can be seen that the performance of ML detector with i.i.d $t$-distributed noise is inferior compared to that with i.i.d Gaussian noise. It can also be seen that smaller the value of $\nu$ (more deviation from Gaussian), more is the degradation in the performance of ML detector. This is mainly because the ML detector in (4) is optimal when the noise is Gaussian distributed and hence deviation from Gaussian distribution results in performance degradation. Whereas, the proposed DNN based detector shows improved BER performance in $t$-distributed noise compared to that in Gaussian noise. As discussed earlier, the reason for this behavior is that the Gaussian noise is the worst case noise among all the noise distributions for a given variance. Therefore, learning in a non-Gaussian noise ($t$-distributed noise in this case) is more effective, which leads to superior BER performance.

V. Conclusions

In summary, due to its inherent ability to effectively learn the underlying noise models in practical receivers, the proposed DNN-based GSM detector (with multiple sub-DNNs to decode active antenna indices and modulation symbols) achieves robust and better bit error performance compared to ML detection performance when deviations from the standard model are witnessed.

REFERENCES