A Deep-learning-based Joint Inference for Secure Spatial Modulation Receiver

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Abstract—As a green and secure wireless transmission way, secure spatial modulation (SM) is becoming a hot research area. Its basic idea is to exploit both the index of activated transmit antenna and amplitude phase modulation (APM) signal to carry messages, improve security, and save energy. In this paper, we reviewed its crucial techniques: transmit antenna selection (TAS), artificial noise (AN) projection, power allocation (PA), and joint detection at desired receiver. To achieve the optimal performance of maximum likelihood (ML) detector, a deep-neural-network (DNN) joint detector is proposed to jointly infer the index of transmit antenna and signal constellation point with a lower-complexity. Here, each layer of DNN is redesigned to optimize the joint inference performance of two distinct types of information: transmit antenna index and signal constellation point. Simulation results show that the proposed DNN method performs 3dB better than the conventional DNN structure and is close to ML detection in the low and medium signal-to-noise ratio regions in terms of the bit error rate (BER) performance, but its complexity is far lower-complexity compared to ML. Finally, three key techniques TAS, PA, and AN projection at transmitter can be combined to make SM a true secure modulation.

I. SECURE SPATIAL MODULATION AND DEEP LEARNING

Spatial modulation (SM) concept was first proposed by Chau and Yu in [1]. They had creatively proposed the concept of SM: carry additive bit information via antenna indices. In [2], the authors made a systematic and in-depth investigation of SM, and officially named it as SM. At the same time, the basic principle of SM was also explained. SM exploits both the index of activated transmit antenna and amplitude phase modulation (APM) signal to carry messages. Compared to Bell Laboratories Layer Space-Time (BLAST) and space time coding (STC), SM system achieves a good balance between spatial multiplexing and diversity. We call it as the third way between BLAST and STC. Compared to BLAST and STC, SM has a good advantage of high energy efficiency (EE) due to the use of less active RF chains. Thus, it is a green wireless transmission technique.

Wireless communication is usually prone to passive eavesdropping and active malicious attacks due to its broadcast characteristics. Although there is a series of mature encryption algorithms in the upper layer of network protocol, it is still fragile in wireless communication. To address this issue, the physical layer security (PLS) technology becomes a nature choice, and enhances its security from the perspective of information theory. PLS has been extensively studied in [3]. PLS will work with traditional cryptography to play a key role and provide an incremental guarantee for the future personal privacy protection and information network security. Working with encryption together, a dual protection of transmitting confidential messages (CMs) will be achieved.

In the past decade, secure modulation emerges as an special form of multiple-input-multiple-output (MIMO). It mainly consists of two types: directional modulation (DM) and secure SM(SSM). DM using beamforming with the help of artificial noise (AN) can securely deliver confidential messages (CMs) to desired users in line-of-sight channel, and is unsuitable for fading channels. Instead, SM is naturally suitable for fading channel.

By introducing security into the SM, it is able to transmit CMs over the fading channel. However, transmitting CMs via SM is an attractive and very important issue [4] [5] [6]. In [5], the authors made an extensive investigation of TAS methods in SSM systems. Then, two high-performance transmission antenna selection schemes: leakage-based and maximum SR, have been proposed to improve the SR performance, and the generalized Euclidean distance-optimized antenna selection method has been generalized to provide a secure transmission. In [6], an active antenna-group (AAG) selection is proposed to maximize the average secrecy rate (SR) in the case of limited active antenna pattern and finite-alphabet inputs.

In SSM, how to optimize and design the AN projection matrix has a substantial impact on the SR performance. In [6], [7], AN was projected onto the null-space of the desired channel to improve the security of communication systems. The main benefit of this scheme is that the AN projection matrix has a closed-form expression. However, such a scheme might cause some secrecy performance loss due to lack a holistic consideration of secure communication systems. In other words, the design of the beamformer of AN in conventional way is merely achieved from the perspective of the desired receiver.

Intelligent communication is considered as one of the mainstream directions of the follow-up development of mobile communication after 5G. The basic idea is to introduce intelligent elements into all layers of mobile communication system, realize the organic integration of mobile communication and artificial intelligence technology, and greatly improve the efficiency of mobile communication system. The previous research results have focused on the application layer and the network layer, and the main idea is to introduce machine learning, especially deep learning (DL), into wireless resource management, channel decoding, and other fields. DL is one of the most important breakthroughs in the field of artificial intelligence in the past decade. The author details the DL algorithms in [8]. It has been successfully applied in many
fields such as computer vision, natural language processing, speech recognition, etc., and has achieved great success. Due to the new features of future communication, such as complex scenes with unknown channel models, high-speed and accurate processing requirements, many scholars have introduced DL into the physical layer of wireless communication [12]. In the physical layer, there is a new trend of combining wireless transmission and DL.

In [10], the authors considered channel estimation for millimeter-wave massive MIMO systems. An approximate messaging network based on learning denoising was proposed for channel estimation, which can learn channel structure and estimate channel from a large amount of training data. In [11], a new framework were proposed for integrating large-scale MIMO and DL to address the problem of channel estimation and DOA estimation [12]. Deep neural network (DNN) is used for offline learning and online learning, and the statistical characteristics of the wireless channel and the spatial characteristics of the angle domain are effectively learned. A novel deep learning assisted sparse coded multiple access scheme is proposed in [13]. By using a DNN-based encoder and decoder adaptively construct a codebook that minimizes the bit error rate in [14].

In Fig. 1 a typical secure SM system is shown. In this figure, four main tools including transmit antenna selection (TAS), beamforming of confidential messages, AN projection, and power allocation (PA) are fully utilized to achieve a SSM. In such a network, at desired receiver, the joint detection of transmit antenna index and signal constellation point is required. Joint detection performance is very important. Conventionally, the optimal maximum likelihood (ML) detector is a natural choice. But, as the number of transmit antennas tends to medium-scale or large-scale or the size of signal constellation goes to medium-scale or large-scale, the ML joint detector is confronted with a complexity bottleneck, i.e., exponential complexity. To reduce the computational complexity of receiver, the DNN-based joint detector is proposed to jointly infer the transmit index and signal constellation point in this paper. Compared to ML, the joint DL detector is low-complexity and reach the optimal performance of ML.

II. SYSTEM MODEL AND TRANSMIT ANTENNA SELECTION

Consider a typical SSM system as shown in Fig. 1. In this system, there is a transmitter (Alice) equipped with $N_t$ transmit antennas. Without loss of generality, when the number of antennas at the transmitter is not a power of two, $N_t = 2^{\lfloor \log_2 N_t \rfloor}$, out of $N_t$ transmit antennas are selected for mapping the bits to the antenna index. The $\log_2 M$ bits are used to form a constellation symbol, where $M$ is the signal constellation size. As a result, the spectral efficiency is $\log_2 N_t + \log_2 M$ bits per channel use (bpcu).

Referring to the secure SM model in [15], the transmit signal vector with the aid of AN can be given by

$$x = \sqrt{\beta P_S} e_n s_m + \sqrt{(1 - \beta) P_S} P_{AN} n$$  \hspace{1cm} (1)$$

where $P_S$ denotes the total transmit power constraint and $\beta$ is the PA factor, $e_n$ is the $n$-th column of identity matrix $I_{N_t}$, and $s_m$ is the digital constellation symbol with a normalized power $E[|s_m|^2] = 1$. Additionally, $P_{AN}$ is the AN projection matrix and $n \in \mathbb{C}^{N_t \times 1}$ is the corresponding AN vector. Then, the receive signal at desired receiver Bob can be formulated as follows

$$y_d = \sqrt{\beta P_S} H_k e_n s_m + \sqrt{(1 - \beta) P_S} H_k P_{AN} n + n_b$$  \hspace{1cm} (2)$$

where $H_k$ are the complex channel gain matrix from Alice to Bob and to Eve, $T_k$ is transmit antenna selection matrix.

Selecting an active antenna group can be adopted to further improve the performance of SM systems. There are several existing TAS methods for secure SM system as follows: random, leakage [4], and generalized Euclidean distance antenna selection (EDAS). For the leakage-based TAS strategies, the signal-to-leakage-and-noise ratio (SLNR) of CM from each transmit antenna is computed and formed a sequence of SLNRs, where SLNR is defined as the ratio of the receive signal power at Bob to the sum of the receive power of CM at Eve, receive AN power, and channel noise variance. Then a low-complexity sorting algorithm places the values of SLNR in decreasing order. The antennas corresponding
antennas associated with the top $N$ SLNRs is chosen, called Max-SLNR \cite{4}. The Max-SLNR can achieve the near-optimal SR performance with a low-complexity.

From the aspect of decoding performance at receiver, generalized EDAS performs best in terms of bit error rate. The generalized EDAS Method is aim to select a TAS pattern of maximizing the minimum Euclidean distance over desired channel or minimizing the minimum Euclidean distance over eavesdropping channel due to the fact that the minimum distance has a direct relationship to BER.

![Fig. 2. Comparison of SR performance of various TAS methods.](image)

Fig. 2 demonstrates the SR performance comparison of the optimal exhaustive search (ES), Max-SLNR, EDAS, and random methods without the aid of AN. From this figure, it is seen that the four methods have a decreasing order in SR performance as follows: ES, Max-SLNR, EDAS, and random method. Additionally, we also find an interesting result: all the SR curves first go up as hills, then reach their peaks, and finally go down hills as SNR increases. In other words, all the SR curves have main peaks, and can be approximately viewed as concave functions of the SNR.

![Fig. 3. Comparison of SR performance of various PA strategies.](image)

Fig. 3 makes a SR performance comparison of ES, Max-SLNR, EDAS, and random methods with the aid of AN. From this figure, it is seen that the four methods have still an decreasing order in SR as follows: ES, Max-SLNR, EDAS, and random. In particular, observing Fig. 2 and Fig. 3 we find an important fact: with the aid of AN, the SR performance can be improved significantly, especially in the medium and high SNR regions. The values of SR for the four methods grows gradually as SNR increases. When SNR enters the high SNR region, their SR performance reaches their corresponding SR cells.

III. Beamforming, AN Projection, and Power Allocation

Since secure SM channel can be viewed as a discrete-input continuous-output memoryless channels (DCMC), it is very hard to find a closed-form expression for mutual information in such a network. Mutual information contains the expected items of noise, usually with high computational complexity. Only in the case that the input is a Gaussian signal, The SR expression will have a very concise form.

For DCMC, in general, an approximate estimation SR expression is used instead of exact SR, it is difficult to convert to a convex problem. There is an inversion in the expression, and the outer layer needs to solve the expectation. This is a rather complicated issue. In addition, it is difficult for the transmitter to optimize the CM beamforming vector and AN projection matrix by maximizing SR. This is a challenging problem in the coming future. However, at the cost of some SR performance loss, some low-complexity and closed-form methods can be used. For example, the AN projection matrix can be constructed from the null-space of the desired channel from Alice to Bob while the CM beamforming vector is also formed from the null-space of the desired channel from Alice to Eve. If you want to further the SR performance, the leakage-based rule is used to optimize the design of AN projection matrix and CM beamforming vector.

PA, as an efficient way to enhance security, has been investigated in \cite{15}. By adjusting the PA factor, the power can be allocated between CM and AN freely to affect the SR and BER performance. By simulation and proof, it confirms that SR is a concave function of the PA factor $\beta$. Although exhaustive search (ES) can be employed to search the optimal PA factor, its computational complexity is high. Thus, in \cite{15}, a novel PA strategy, called Max-P-SINR-ANSNR where ‘P’ is short for product, and ‘ANSNR’ stands for AN-to-signal-plus-noise ratio, presented a closed-form expression for the PA factor. This dramatically reduces the complexity of ES.

![Fig. 4 makes a comparison of several typical PA strategies: ES, fixed, gradient descent (GD), and Max-P-SINR-ANSNR.](image)

Fig. 4 makes a comparison of several typical PA strategies: ES, fixed, gradient descent (GD), and Max-P-SINR-ANSNR. From this figure, it follows that the Max-P-SINR-ANSNR and GB strategies in \cite{15} are close to the optimal ES, but their complexity is dramatically lower than ES. Comparing the three methods with fixed power allocation factors, it can be seen that the SR at $\beta = 0.5$ is the lowest one, and $\beta = 0.1$ is the highest one in the value of high SNR. This is because when the SNR is
high, both Bob and Eve have a very good quality of channel, and a large portion of transmit power may be allocated to AN to disturb eavesdropper, so as to obtain a high security performance. Additionally, due to its closed-form expression of Max-P-SINR-ANSNR, it strikes a good balance between complexity and performance.

IV. PROPOSED DNN-BASED JOINT INFERENCE OF ANTENNA INDEX AND CONSTELLATION POINT

Assuming Bob has the perfect channel state information (CSI) of \( \mathbf{H} \) and \( T_k \), the joint ML detector (MLD) at desired receiver can be casted as follows

\[
[h_k, \hat{m}_k] = \arg\min_{n \in [1,N_c], m \in [1,M]} \| y_d - \sqrt{\beta}P_S \mathbf{H} \mathbf{T}_k \mathbf{e}_n \mathbf{s}_m \|_2^2
\]

where \( h_k \) and \( \hat{m}_k \) denote the index of transmit antenna and signal constellation point by joint MLD, respectively. The MLD requires the computational complexity \( N_{TAS} \times N_{SC} \) floating-point operations (FLOPs) where \( N_{TAS} \) and \( N_{SC} \) denote the complexity of TAS scheme and the constellation size, respectively. Obviously, this complexity is a product. As \( N_{TAS}, N_{SC} \) or both tends to large-scale, the total complexity will become a large number.

To reduce this complexity, a DNN is a natural choice due to the fact that determining which antenna or constellation point is actually a kind of classifying. However, the conventional DNN structure shown in Fig. 5, locating on the right-upper corner, is verified to be 3dB worse than the ML in terms of BER given a fix BER=10^{-3}. To completely remove the 3dB performance gap, a novel DNN structure shown in the left-bottom corner of Fig. 5 is proposed. Here, each layer is redesigned to have three kinds of outputs: \( S_k \), \( E_k \) and \( V_k \), where \( S_k \) and \( E_k \) are the estimate of constellation symbol and antenna index in the \( k \)-layer, respectively. \( V_k \) is the hidden output vector of the \( k \)-layer, and is also the input of the next layer. The DNN-based joint inference idea is to minimize the loss function

\[
\| x - \hat{x}(y_d, \mathbf{H}) \|_2^2 = \| x - F(y_d, \mathbf{H}; \mathbf{w}, \mathbf{b}) \|_2^2
\]

by random GD and back-propagation methods, where

\[
F(y_d, \mathbf{H}; \mathbf{W}, \mathbf{b}) = \mathbf{F}^{n-1}(\mathbf{W}^{n-1}F^{n-2}(\ldots (\mathbf{W}^1F^0(y_d) + \mathbf{b})^0 + \cdots ) + \mathbf{b}^{n-1})
\]

, where \( \mathbf{W}^k \) is the matrix of weight coefficients corresponding to layer \( k \), and \( \mathbf{b}^k \) stands for the bias vector for the corresponding layer. \( \mathbf{f}^{(k)}(\cdot) \) represents nonlinear activation function of layer \( k \) and describes an input-output mapping. \( \text{Vec}(\mathbf{H}) \) is the vectorization of the matrix \( \mathbf{H} \)

To solve the gradient disappearance problem, some new activation functions are adopted to replace the classical sigmoid activation function. Among them, the Rectified Linear Unit (ReLU) is commonly used. Introducing nonlinearity by zeroing a function value less than zero. When the input value is greater than zero, the function is a linear function, which simplifies the gradient calculation and the gradient value will not decrease with the increase of the input. This alleviates the gradient disappearance problem.

To speed up the convergence and reduce the computational complexity, the classical DG algorithm adjusts to the fall of the stochastic gradient, that is, randomly selects a sample to calculate the loss function and the gradient. However, the random selection of sample selection causes a large volatility in the training process, that is, the network cannot converge to the optimal solution, but fluctuates around the optimal solution. Take a compromise, using a batch gradient descent method, each time a batch of samples is selected to calculate the loss function and gradient. It’s also not guaranteed to be globally optimal by this method, but we can receive this solution as the loss function is reduced to be small.

Even using the above two strategies, neural networks are not very easy to train. Then, some of the current popular neural network training techniques can be adopted to improve its performance, speed and stability. The use of a moving average model enhances the stability of the parameters. Dropping out units (both hidden and visible) by a probability when training neural networks can efficiently address the problem of network over-fitting and improve its generalization ability. Additionally, the batch normalization is applied to improve the performance.

Now, we present numerical results to validate the effectiveness of our proposed DNN-based scheme. Constructing training and validation sets: generating a large amount of training data by performing baseband numerical simulation on the SM-MIMO channel model, and performing two-dimensional labeling of the antenna and the constellation point on the received vector data. The structure of the neural network depth and the number of neurons per layer are determined by initializing the weight matrix and bias of the network. Then hyperparameters: maximum number of training, batch size, initial learning rate, and drop probability, are also initialized. The network is trained by training set, and the verification set is used to verify the network after every 100 iterations to decide whether to terminate early. Apply the above learning completion network to a desired receiver of SM to verify its BER performance.
Fig. 5. Proposed novel DNN structure for joint inference of antenna index and constellation point.

Fig. 6. BER performance comparison among proposed DNN, joint ML, conventional DNN, ZF, and MMSE with $N_t=4$, $N_r=4$ and QPSK.

V. OPEN PROBLEMS

There are still many open problems existed to be addressed. Here, we list several important ones as follows:

1) As the number of antennas at SM transmitter tends to large-scale, the circuit cost and complexity becomes a significant obstacle for practical applications of SM. A hybrid analog-digital structure is preferred. In such a scenario, how to achieve an optimal strategy of transmit antenna subarray is the challenging problem. This problem can be modelled an integer optimization problem. The key is to develop a low-complexity algorithm.

2) If Eve works in a full-duplex model and becomes an active eavesdropper, i.e., jamming, how to optimize the design of the transmitter at Alice in order to reduce the effect of jamming from Eve and at the same time achieve a feasible performance is a hard task. For Bob, the receive beamforming scheme of combating the jamming is preferred.

3) By adjusting the neural network structure of deep learning, the BER performance of the proposed structure with QPSK is close to the performance of ML detection. To extend it to the high-order modulation is still an open problem. This requires us to optimize the structure of deep learning.

4) In the presence of CSI measurement errors, how to construct robust beamforming, PA, and TAS by taking the statistical property of CSI error into account requires a great effort. In particular, the first task is to formulate the SR expression or approximate expression in such a scenario. This will pave a way for robust beamforming, PA, and TAS.

5) Due to non-convexity of the SR expression, AN optimization is a challenging task because the beamformer of AN is always included in a complicated expression,
especially when a rough/statistic CSI of Eve’s channel is available at the transmitter.

6) As the number of TAs further increases, how to optimize an AAG for enhancing the security of the communication systems becomes intractable, this is because the computational complexity of evaluating the accurate SR will be explosively grown upon increasing the number of TAs. That requires us exploring some concise metrics instead of the original function to evaluate the value of SR.

VI. CONCLUSION

In this article, the great potential of secure SM has been highlighted as a key secure tool for future vehicular communications, IoT, UAV, smart transportation, and satellite communications. We review its key techniques: TAS schemes, PA strategies, and joint detection methods at desired receiver. A new DNN structure was proposed to jointly infer the transmit strategies, and joint detection methods at desired receiver. A new DNN structure was proposed to jointly infer the transmit antenna index and signal constellation point, i.e., a new joint detection way with low-complexity. Also, we have raised several new open important future research problems. Finally, in our view, secure SM will have wide diverse promising applications in the near future.

REFERENCES

[1] Y. A. Chau and Shi-Hong Yu, “Space modulation on wireless fading channels,” in IEEE 54th Vehicular Technology Conference. VTC Fall 2001. Proceedings (Cat. No.01CH37211), vol. 3, Oct 2001, pp. 1668–1671 vol.3.
[2] R. Y. Mesleh, H. Haas, S. Sinanovic, C. W. Ahn, and S. Yun, “Spatial modulation,” IEEE Trans. Veh. Technol., vol. 57, no. 4, pp. 2228–2241, July, 2008.
[3] W. Trappe, “The challenges facing physical layer security,” IEEE Commun. Mag., vol. 53, no. 6, pp. 16–20, June 2015.
[4] F. Shu, Z. Wang, R. Chen, Y. Wu, and J. Wang, “Two high-performance schemes of transmit antenna selection for secure spatial modulation,” IEEE Trans. Veh. Technol., vol. 67, no. 9, pp. 8969–8973, Sep. 2018.
[5] F. Shu, X. Wu, J. Lu, C. Chen, and J. Wang, “Secure and precise wireless transmission for random-subcarrier-selection-based directional modulation transmit antenna array,” IEEE J. Sel. Areas Commun., vol. 36, no. 4, pp. 890–904, Apr. 2018.
[6] G. Xia, F. Shu, Y. Zhang, J. Wang, S. ten Brink, and J. Speidel, “Antenna selection method of maximizing secrecy rate for green secure spatial modulation,” IEEE Trans. Green Commun and Netw., vol. 3, no. 2, pp. 288–301, Jun. 2019.
[7] F. Wu, L. Yang, W. Wang, and Z. Kong, “Secret precoding-aided spatial modulation,” IEEE Commun. Lett., vol. 19, no. 9, pp. 1544–1547, Sep. 2015.
[8] J. Schmidhuber, “Deep learning in neural networks: An overview,” Neural Netw., vol. 61, pp. 85–117, 2015.
[9] C. Jiang, H. Zhang, Y. Ren, Z. Han, K. Chen, and L. Hanzo, “Machine learning paradigms for next-generation wireless networks,” Wireless Commun., vol. 24, no. 2, pp. 98–105, Apr. 2017.
[10] H. He, C. Wen, S. Jin, and G. Y. Li, “Deep learning-based channel estimation for beamspace mmwave massive mimo systems,” IEEE Wireless Communications Letters, vol. 7, no. 5, pp. 852–855, Oct. 2018.
[11] E. Nachmani, Y. Be’ery, and D. Burstein, “Learning to decode linear codes using deep learning,” in 2016 54th Annual Allerton Conference on Communication, Control, and Computing (Allerton), Sep. 2016, pp. 341–346.
[12] H. Huang, J. Yang, H. Huang, Y. Song, and G. Gui, “Deep learning for super-resolution channel estimation and DOA estimation based massive MIMO system,” IEEE Trans. Veh. Technol., vol. 67, no. 9, pp. 8549–8560, Aug. 2018.
[13] M. Kim, N. Kim, W. Lee, and D. Cho, “Deep learning-aided scma,” IEEE Commun. Lett., vol. 22, no. 4, pp. 720–723, Apr. 2018.
[14] E. Nachmani, E. Marciano, L. Lugosch, W. J. Gross, D. Burstein, and Y. Beery, “Deep learning methods for improved decoding of linear codes,” IEEE J. Sel. Topics Signal Process., vol. 12, no. 1, pp. 119–131, Feb. 2018.
[15] F. Shu, X. Liu, G. Xia, T. Xu, J. Li, and J. Wang, “High-performance power allocation strategies for secure spatial modulation,” IEEE Trans. Veh. Technol., vol. 68, no. 5, pp. 5164–5168, May 2019.

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