Spatial Modulation: an Attractive Secure Solution to Future Wireless Network

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Abstract—As a green and secure wireless transmission method, 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 signal to carry messages, improve security, and save energy. In this paper, we review its crucial challenges: transmit antenna selection (TAS), artificial noise (AN) projection, power allocation (PA) and joint detection at the desired receiver. As the size of signal constellation tends to medium-scale or large-scale, the complexity of traditional maximum likelihood detector becomes prohibitive. To reduce this complexity, a low-complexity maximum likelihood (ML) detector is proposed. To further enhance the secrecy rate (SR) performance, a deep-neural-network (DNN) PA strategy is proposed. Simulation results show that the proposed low-complexity ML detector, with a lower-complexity, has the same bit error rate performance as the joint ML method while the proposed DNN method strikes a good balance between complexity and SR performance.

Index Terms—Spatial modulation, secrecy rate, artificial noise, power allocation, deep-neural-network.

I. SECURE SPATIAL MODULATION AND DEEP LEARNING

Spatial modulation (SM) concept was first proposed by Chau and Yu in [1]. Its main idea is to carry additive bit information via antenna indices. In [2], the authors made a systematic and in-depth investigation of SM. Until now, the basic principle of SM was also extended to index modulation. SM exploits both the index of activated transmit antenna and amplitude phase modulation signal to carry messages. Different from Bell Laboratories Layer Space-Time (BLAST) and space time coding (STC), SM may strike a good balance between spatial multiplexing and diversity and is called the third way between BLAST and STC. Compared to BLAST and STC, SM has a merit of high energy efficiency due to the use of less active radio frequency (RF) chains. Thus, it is also a green wireless transmission technique.

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Wireless communication is usually prone to passive eavesdropping and active malicious attack due to its open broadcast characteristics. Although there is a series of mature encryption algorithms in the upper layer of network protocol, it is still possible to be broken in wireless communication if the eavesdropper has a strong computational ability. To address this problem, the physical layer security (PLS) technology becomes an inevitable choice to work with traditional encryption methods to provide a double layer protection on confidential message (CM), and enhances wireless security from the perspective of information theory. PLS has been extensively studied in [3]. PLS actually provides an incremental guarantee for the future personal privacy protection and information network security.

Recently, secure modulation has emerged as an special form of multiple-input-multiple-output (MIMO). It is mainly composed of two categories: directional modulation (DM) and secure SM (SSM). DM, with the help of artificial noise (AN), can securely deliver CM to desired user in line-of-sight channel by beamforming, and is unsuitable for fading channels. Conversely, SM is naturally suitable for fading channel.

Transmitting CM via SM is an attractive and very important issue [4], [5]. In [4], the authors have made a wide and in-depth investigation of transmit antenna selection (TAS) methods in SSM systems. Then, two high-performance TAS schemes: leakage-based and maximum secrecy rate (SR), have been proposed to improve the SR performance, and the generalized Euclidean distance-optimized antenna selection (EDAS) method has been extended to provide a secure transmission. In [5], an active antenna-group selection was proposed to maximize the average SR for limited active antenna pattern and finite-alphabet inputs.

In SSM, how to construct a proper AN projection matrix has an important impact on the SR performance. In [5], [6], AN was projected onto the null-space of the desired channel to improve the SR performance. Here, the major benefit of this scheme is the fact that the AN projection matrix has a closed-form expression and is of low-complexity. However, such a scheme might result in some secrecy performance loss.

Intelligent communication has been considered as one of the mainstream directions of the coming future development of wireless communication. Its basic idea is to introduce intelligent elements into all layers of wireless networks, so as to realize the organic integration of wireless networks and artificial intelligence technology, and greatly improve the efficiency and performance of wireless networks. The existing...
research results have concentrated on the application layer, physical layer, and the network layer. The main idea is to introduce machine learning, especially deep learning (DL), into wireless resource management, channel decoding, and other fields.

The DL has been successfully and widely applied in many fields such as computer vision, natural language processing, speech recognition, etc., and has achieved great success. Due to the new features and challenges of future wireless 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 [1]. In the physical layer, there is a new tendency of combining wireless transmission and DL. In [2], 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 [3], a new framework was proposed for integrating large-scale MIMO and DL to address the problem of channel estimation and direction of arrival estimation.

In Fig. 1 a conventional SSM system is presented. In this figure, four important tools including TAS, beamforming of CMs, AN projection, and power allocation (PA) are fully employed to achieve a high-performance SSM. In such a system, at desired transmitter, the PA of maximizing SR is a hard problem considering the fact that the expression of SR has no closed-form. In other words, SR is a non-linear function of PA factor. Exhaustive search (ES) can achieve the optimal SR performance with a sufficient small bin width. To reduce the computational complexity and approach the optimal SR performance, a deep neural network (DNN) based PA strategy is proposed to implement PA between AN and CM given the known beamforming vector and AN projection matrix. With a slight SR performance loss, the proposed DNN-based PA method is of lower-complexity than ES.

II. SYSTEM MODEL AND TRANSMIT ANTENNA SELECTION

Consider a typical SSM system as shown in Fig. 1 where the transmitter (Alice) is equipped with $N_a$ transmit antennas (TAs). According to the nature of SM, when the number of TAs is not a power of two, $N_t = 2^\left\lfloor \log_2 N_a \right\rfloor$ out of $N_a$ TAs have to be selected for mapping binary bits to the antenna index. Moreover, $\log_2 M$ bits are used to form a constellation symbol and $M$ is the size of the adopted signal constellation. As a result, the achievable spectral efficiency arrives at $\log_2 N_t + \log_2 M$ bits per channel use.

 Appropriately selecting out an active antenna group is capable of improving the security performance of SM systems. As a matter of fact, there exist a number of TAS methods for enhancing the secrecy performance of SSM, such as random, leakage [4], and generalized EDAS. For the leakage-based TAS strategies, the signal-to-leakage-and-noise ratio (SLNR) of CM from each transmit antenna is calculated and sorted, where the SLNR is defined by 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 all the SLNRs in a decreasing order. Upon choosing the antennas associating with the top $N$ SLNRs, the so-called Max-SLNR method is established [4]. The Max-SLNR has a ability of approaching the near-optimal SR performance with a low computational complexity.

From the perspective of the decoding performance at a receiver, generalized EDAS performs best in terms of bit error rate (BER). The generalized EDAS method aims for selecting out a TAS pattern by maximizing the minimum Euclidean distance over the desired channel or minimizing the minimum Euclidean distance over eavesdropping channel, the core principle is that the minimum distance has a direct impact of BER performance.

Fig. 2 shows a comparison of the SR performances of the optimal ES, Max-SLNR, EDAS, and random method with $N_a = 15$, $N_t = 8$, $N_b = N_e = 2$. From this figure, it can be observed that the four methods have a decreasing order in the 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 the SNR increases. In other words, all the SR curves have crest values, and can be regarded as concave functions of the SNR.

III. PROPOSED DNN-BASED PA STRATEGY

How to allocate power among CM and AN will have a dramatic impact on the SR performance. PA, as an efficient way to enhance security in SM system, has been investigated in [10], where two high-performance PA strategies were proposed to achieve substantial SR gains over existing PA methods. The optimal PA factor between signal and interference transmission can be determined by exhaustive search for SM system. However, there is no closed-form SR expression in discrete-input continuous-output memoryless channels, which results in a high computational complexity to complete SR. In addition, small search step size also leads to a high computational complexity of ES. To reduce the computational complexity, an approximate SR (ASR) expression is used instead of exact SR. Then, gradient descent (GD) algorithm is adopted to solve the PA factor.

To make a complete comparison among existing methods and the proposed DNN in this section, simulation parameters are set as follows: \(N_a = N_t = 4\), \(N_b = N_e = 2\). Fig. 3 makes a comparison of several typical PA strategies: ES, fixed, ASR-GD, Max-P-SINR-ANSNR, and proposed DNN. Comparing the three methods with fixed PA 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. Correspondingly, when the SNR is low, a high portion of transmit power should be allocated to CM to improve Bob’s reachable rate, so as to achieve a high security performance.

As shown in Fig. 3, the SR performance of ASR-GD is close to that of ES method. However, to evaluate the expression of ASR is still high-complexity. The authors in [10] analyzed the problem in terms of the power of the received signal and noise, and proposed 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. As shown in Fig. 3 the SR performance of the proposed Max-P-SINR-ANSNR is close to that ASR-GD, but with extremely low complexity.

![Fig. 2. Comparison of SR performance of various TAS methods.](image1)

![Fig. 3. Comparison of SR performance of various PA strategies.](image2)

![Fig. 4. Diagram of the deep neural network.](image3)
of the FC layer. Finally, the DNN outputs the predicted value of PA.

In addition to the influence of network structure, the performance of DNN largely depends on the constructed training data set and its training method. First, the channel state information (CSI) of the desired and eavesdropping users obeying Rayleigh distribution are randomly generated, and then the optimal PA factor is solved by ES method as a label. The set of CSI and PA factor are used as the training data set, and then Adam optimizer is used to train DNN off-line. The trained DNN is used to predict the PA factor based on the newly input CSI about the desired user and the eavesdropping receiver. As shown in Fig. 3, the SR performance of the proposed DNN is close to that of ASR-GD algorithm, and strikes a good balance between complexity and performance.

IV. PROPOSED LOW-COMPLEXITY ML DETECTOR

In [11], the authors proposed an optimal joint ML detector. Here, Bob is assumed to have the perfect knowledge of H and S where H denotes the channel from Alice to Bob and S is the associated antenna selection matrix. This joint ML detector can reach an optimal BER performance but it needs exhaustive search among all possible antennas and symbols to infer the most likely solution, which requires a high computational complexity, especially in large-scale signal constellation. To reduce computational complexity, a sub-optimal method with low-complexity in [12] was proposed but had a far worse BER performance than joint ML. To address this dilemma, a new low-complexity ML detector is proposed by us to approach the ML performance in this paper. It utilizes the CSI and received signal to detect the symbol, and then combines the symbol and CSI to estimate the antenna index. The corresponding flowchart for the proposed method is plotted in Fig. 5.

The whole process for our proposed method can be described as follows. First, we initialize the estimated symbol $x_l$, estimated antenna index $l$, and the minimum Euclidean distance $d_{min}$, where $h_j$ is the $j$th column of $H$ and $y$ represents the received signal vector. For all $N_t$ transmit antennas, we traverse these transmit antennas to calculate the corresponding $g_j$, which is used to demodulate the transmit symbol $x_l$. $Q(\cdot)$ and $D(\cdot)$ represent the quantization and demapping functions, respectively. The latter maps the quantized value to the nearest constellation points. Then the Euclidean distance $d_j$ between receiver signal $y$ and the estimated symbol $x_l$ is computed. If $d_j$ is less than the predefined $d_{min}$, it means this process can terminate and we will update all the original values. If not, we will move to the next antenna index until all $N_t$ transmit antennas are traversed.

To make a comparison among the computation complexities of the low-complexity ML detector proposed by us, ML and suboptimal methods, we take the number of complex multiplications (CMs) as a performance metrics. As in these two processes, the numbers of complex additions for all methods are identical, therefore, we omit the number of additions here. Using the results in [11], their complexities are follows: $C_{ML} = 2N_t N_r + 2N_t M + M$ CMs, $C_{Proposed} = 2N_t N_r + N_t \log_2 M + 2N_t$ CMs, and $C_{Suboptimal} = 2N_t N_r + N_t + M$ CMs. Obviously, the proposed method has much lower computational complexity than the ML method as the number of constellation points tends to large-scale.

![Fig. 5. Block diagram of the proposed low-complexity ML detector.](image)

![Fig. 6. Comparison of BER performance in SM system employing different detection.](image)
power being 4W, $N_t=4$, $N_r=4$, modulation 16 QAM or 256 QAM modulation. Fig. 6 plots the curves of BER versus SNR for three detectors. From both 16 QAM and 256 QAM, it is clearly seen that the proposed low-complexity ML detector achieves the same BER performance as the joint ML and far better than suboptimal method. Specially, the proposed detector harvests a SNR gain of 2.5dB at BER=$10^{-2}$ over the sub-optimal detection for 16 QAM. As the BER increases, the SNR performance gain increases gradually. For 256 QAM, the SNR performance becomes significant. At BER=$10^{-2}$, the proposed detector achieves a SNR gain of 8dB over sub-optimal method.

V. SPATIAL MODULATION AND INTELLIGENT REFLECTING SURFACE

Communications with intelligent reconfigurable surface (IRS) have been regarded as a promising candidate technology for future wireless networks. An IRS is an electromagnetic two-dimensional surface, composed of a large number of low-cost nearly-passive reconfigurable reflecting elements. Equipped with a smart controller, the IRS is able to intelligently adjust the phases of incident electromagnetic waves to increase the received signal energy, expand the coverage region, and alleviate interference, so as to enhance the communication quality of the wireless networks.

As mentioned above, SM is a special MIMO technology which activates one transmit antenna with one transmit antenna and exploits the index of the active antenna for information transfer. The undeniable potential of both SM and IRS based communication schemes has been the main motivation of this part.

The concept of IRS-assisted communications was first brought to the realm of SM in [13]. In [14], the authors applied SM principle to the IRS by adjusting the ON (active) and OFF (inactive) status of each reflecting element. Therefore, the IRS can deliver additional information by adopting SM on the index of the reflecting elements. In [13], the authors investigated the IRS-aided receive SM (RSM) technique. Inspired by [13], the authors in [15] extended its structure to combine the transmit and receive antenna indices for joint spatial modulation by shaping the reflecting beam with IRS. It is worth mentioning that conventional SM cannot combine transmit SM and RSM at the same time, due to the limitation of a single activated transmit antenna.

In [13]–[15], it has been shown that the IRS-assisted SM system outperforms, in terms of achievable rate and BER, the conventional SM system. Additionally, there is scarce existing literature studying the SR performance of IRS-assisted SSM system, which might be an potential way to make a significant improvement in SR performance.

VI. OPEN PROBLEMS

There are still so many open existing problems to be addressed in SSM. In what follows, several important ones of them are summarized:

1) If Eve works at a full-duplex model, she will become an active eavesdropper, i.e., a fixture of Mallory plus Eve. In such a situation, it is particularly important 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. This is a hard task. For Bob, the receive beamforming scheme should be well designed to combat the jamming.

2) 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 derive the SR closed-form expression or approximate expression in such a situation. This will pave a successful way for robust beamforming, PA, and TAS.

3) As the number of transmit antennas at transmitter tends to massive, the circuit cost and complexity becomes prohibitive for future practical applications of SM. Introducing hybrid analog and digital MIMO structure into SM is an efficient way to reduce the detection complexity and exploit the spatial diversity gain from MIMO. This will make a good balance among circuit cost, computational complexity and secure performance.

4) Currently, IRS is popular, combining IRS with SM is a new trend. This will open a new life for SM. How to establish the system model of secure IRS-aided SM is changeling. Based on this, it is also nontrivial to derive the closed-form expression and upper bound of SR. Finally, it is extremely important for how to optimize the choice of IRS elements under the criterion of maximizing SR.

VII. CONCLUSION

In this paper, the great potential of SSM has been highlighted as a key secure tool for future wireless networks such as vehicular communications, internet of things, unmanned aerial vehicle, smart transportation, and satellite communications. We reviewed its key techniques: beamforming, TAS, PA, and detection at desired receiver. A DNN-based PA was proposed to achieve the SR performance close to the optimal one. Then, a low-complexity ML detector is proposed to achieve the optimal BER performance of joint ML. Also, several new important future research problems are raised for SSM. Finally, it is pointed out that SSM will have several diverse promising applications in the coming 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] 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.
[6] 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.

[7] 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.

[8] 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.

[9] E. Nachmani, Y. Be’ery, and D. Burshtein, “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.

[10] 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.

[11] J. Jeganathan, A. Ghrayeb, and L. Szczecinski, “Spatial modulation: optimal detection and performance analysis,” *IEEE Commun. Lett.*, vol. 12, no. 8, pp. 545–547, 2008.

[12] R. Mesleh, H. Haas, C. W. Ahn, and S. Yun, “Spatial modulation - a new low complexity spectral efficiency enhancing technique,” in *2006 First International Conference on Communications and Networking in China*, 2006, pp. 1–5.

[13] E. Basar, “Reconfigurable intelligent surface-based index modulation: A new beyond mimo paradigm for 6g,” *IEEE Trans. Commun.*, vol. 68, no. 5, pp. 3187–3196, 2020.

[14] W. Yan, X. Yuan, Z. Q. He, and X. Kuai, “Passive beamforming and information transfer design for reconfigurable intelligent surfaces aided multuser MIMO systems,” *IEEE J. Sel. Areas Commun.*, vol. 38, no. 8, pp. 1793–1808, 2020.

[15] T. Ma, Y. Xiao, X. Lei, P. Yang, X. Lei, and O. A. Dobre, “Large intelligent surface assisted wireless communications with spatial modulation and antenna selection,” *IEEE J. Sel. Areas Commun.*, vol. 38, no. 11, pp. 2562–2574, 2020.

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