


Proceedings

Spatial Modulation for Beyond 5G Communications: Capacity Calculation and Link Adaptation [†]

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Abstract: Spatial Modulation (SM) is a candidate modulation scheme for beyond 5G communications systems due to its reduced hardware complexity and good trade-off between energy and spectral efficiency. This paper proposes two Machine Learning based solutions for easing the implementation of adaptive SM systems. On the one hand, a shallow neural network is shown to be an accurate and simple method for obtaining the capacity of SM. On the other hand, a deep neural network is proposed to select the coding rate in practical adaptive SM systems.

Keywords: link adaptation; adaptive coding and modulation; spatial modulation; 5G; neural networks; machine learning; deep learning

1. Introduction

Future mobile cellular networks need not only to increase their capacity, to be able to transport all the future data traffic; but also to improve their energy efficiency, to save battery and reduce the high power consumption of base stations. One key technology at the physical layer level in 5G is MIMO (Multiple Input Multiple Output), which leverages several antennas at both transmitter and receiver. One modulation scheme for this multiantenna scenario is Spatial Modulation (SM) and its many variants. SM increases the capacity compared with single antenna systems and, in addition, a significant enhancement in the energy efficiency is achieved compared with other MIMO techniques. For this reason, SM scheme is considered for future 5G systems.

All modern digital communication systems allow to tune some transmission parameters in order to adapt to the changing channel conditions and provide the highest throughput to the users. A technology named Link Adaptation or Adaptive Coding and Modulation (ACM) is behind this adaptation, allowing to change the bit rate offered to the users dynamically. This work presents some novel ACM techniques which can be used in beyond 5G systems which make use of SM.

2. System Description

SM is a family of multi-antenna modulation schemes where information is transmitted not only by modulating the amplitude, phase and/or frequency of a sinusoidal carrier, but also by selecting the antenna or group of antennas employed to transmit the modulated symbols. In the simplest scheme, there is just one Radio Frequency (RF) chain, and only one antenna is activated at each time instant, reducing both the transmitter complexity and the power consumption. Despite of this, it allows to transmit information using also all the rest of silent antennas. The more antennas you have, the higher the bit rate you can achieve at a lower energy cost. If M denotes the size of the constellation and N_t the number of transmit antennas, a spectral efficiency of $\eta = \log_2 N_t + \log_2 M$ bits/s/Hz can be achieved with SM.

Figure 1 shows a block diagram of a 2×2 adaptive SM system with ACM which allows to change both the coding rate r of the channel encoder and the modulation order M . The adaptation of the physical layer parameters allows to follow the time variant channel with the aim of approaching the transmission bit rate as much as possible to the instantaneous channel capacity.

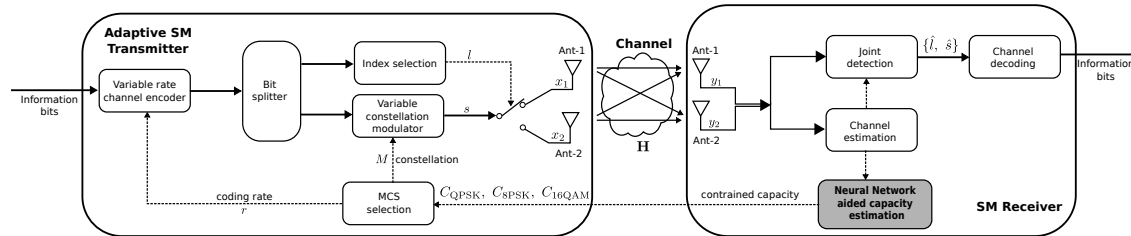


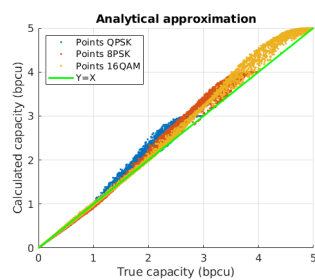
Figure 1. Block diagram of an adaptive SM system with ACM.

3. Capacity Calculation of SM Systems

The capacity of SM depends on the SNR γ and the channel matrix \mathbf{H} . Therefore, whilst a mobile user is moving with his smartphone around the city, the strength of the received signal and the environment surrounding the gNB and the UE antennas will impact the capacity and, in consequence, the maximum bit rate that the user can get.

There is not a closed form expression for the SM capacity although this can be calculated by means of Monte Carlos simulations. To reduce its computation time, some analytical approximations of the SM capacity constrained to a given constellation were proposed. However, those expressions still entail a high complexity and, in addition, they have a problem of overestimation of the true capacity for some channels.

To avoid these issues, a Machine Learning (ML) approach was applied successfully to compute the SM capacity [1]. A Multilayer Feedforward Neural Network (MFNN) was trained with supervised learning to perform the mapping between the channel conditions, (γ, \mathbf{H}) , and the constrained capacity of SM for several constellations. A single hidden layer MFNN with a specif set of input features extracted from the SNR and the channel matrix was enough to outperform previous analytical approximations, both in terms of accuracy and complexity, as can be seen in Figure 2.



(a) Prior approximation

		Taylor approx.	MFNN	Factor
Complexity	Real products	7,168	368	$\div 20$
	Non linear op.	2,128	23	$\div 92$
	Execution time	5.47 ms	0.107 ms	$\div 51$
Accuracy	3σ	0.392	0.018	$\times 22$

(b) Comparison between MFNN and prior analytical approx.

Figure 2. Performance comparison of the previous analytical approximations and the MFNN for obtaining the constrained capacity of SM with three constellations (QPSK, 8PSK and 16QAM).

4. Coding Rate Selection with a Deep Neural Network

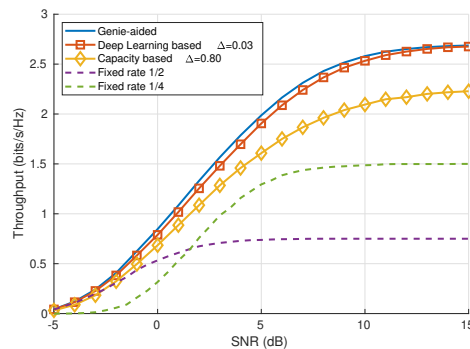
The coding rate selection in a practical SM system can be done with the capacity calculated by the neural network if a proper back-off margin Δ is subtracted from the theoretical capacity. In Figure 3b the throughput achieved with this ACM mechanism is referred as capacity based. Nevertheless, a neural network can be trained for making the coding rate selection directly [2]. In this Deep Learning

(DL) based approach, a MFNN of three hidden layers learns the mapping from the channel conditions to the optimum coding rate.

Figure 3b compares the throughput of different adaptive and non adaptive SM systems. For bounding the error rate, a non adaptive system should use a low coding rate that, as can be seen in the plot, limits considerably the achievable throughput. On the other hand, the selection based on the calculated capacity represents clearly a great improvement. However, the DL based mechanism outperforms all the other methods, achieving the highest throughput and being very closed to the ideal genie-aided coding rate selection.

PARAMETER	VALUE
Antennas	$N_t = 2, N_r = 2$
Constellation	QPSK ($M = 4$)
Channel coding	DVB-S2 (BCH + LDPC)
Number of coding rates	$K = 9$ from 1/4 to 9/10
Target BER	$p_0 = 10^{-4}$
Channel matrices	Rayleigh distributed
SNR range	-5 to 15 dB

(a) System parameters



(b) Throughput comparison

Figure 3. System parameters, classification performance of the DL-based coding rate selection and throughput obtained with different adaptive and non adaptive SM coding rate selection mechanisms.

5. Conclusions

In this article our recent contributions regarding the adaptation of SM systems were briefly presented. These embrace the capacity calculation of SM by means of a neural network and the coding rate selection in practical SM systems with a deep neural network. Thus, a link adaptation method is proposed for SM, a sort of modulation scheme considered for beyond 5G systems due to its good trade-off between complexity and spectral and energy efficiency.

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Conflicts of Interest: The authors declare no conflict of interest.

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