Toward Anti-Jamming Constellations via Adversarial Reinforcement Learning

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To ensure the service reliability of modern communication, it needs to resist various types of jamming in the wireless channel. Thus appropriate modulation design is the key means to ensure a low bit error rate. Due to the complexity and variability of the channel environment, a simple preset constellation is difficult to adapt to all scenarios, and the online constellation optimization method based on reinforcement learning shows its potential [1, 2]. However, the existing methods need to select the appropriate noise level with many experiments and rich experience. Even if it is well selected, it can not ensure the optimal convergence and stability of the results

In the research concerning adversarial training, scholars believe that attacks with appropriate strength are very important [3]. The adversarial jamming method can find the best jamming waveform with the lowest power [4]. Based on the above ideas, we propose an adversarial reinforcement learning method for designing the optimal anti-jamming modulation. The core idea is to introduce the best jamming waveform, that is, to adaptively select the lowest necessary jamming power and randomly select the jamming waveforms in different directions with similar power. Through this core improvement, our method can quickly make the model converge to the optimal solution.

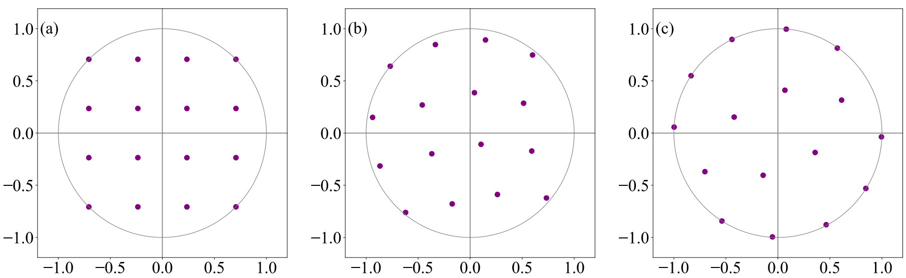

Figure 1. Comparison of different modulation constellations under maximal power constraints: (a) 16QAM modulation, (b) the modulation obtained by reinforcement learning, and (c) the modulation obtained by our method.

We compare modulation constellations obtained by different methods in Figure 1. As the signal-to-noise ratio is 11.5dB, the bit error rate of 16QAM is 0.00462, which for reinforcement learning, is 0.00365 and is slightly lower than 16QAM. However, the bit error rate of our method can reach as low as 0.00170. Compared with reinforcement learning, the constellation obtained by our method is more regular and the spacing of each point is larger. More technical details and results will be exchanged during future conferences.

References

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