Research on Anti-jamming Algorithm of Multi-antenna System Based on Artificial Intelligence Technology

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Abstract. In order to solve the system interference problem caused by beamforming technology of multi-antenna system, an anti-jamming solution based on artificial intelligence technology is proposed, and a multi antenna anti-jamming model based on artificial intelligence algorithm is constructed. PSO algorithm is adopted to train and verify the rationality, convergence ability and performance of the model. Finally, the antenna array will form a great gain in the desired direction to improve the desired signal, while it will form a zero notch at the interference direction for interference suppression. It effectively improves the SINR (signal to interference ratio) of the receiver, and then improves the system performance and increase the system capacity.

Keywords: Multi-antenna system · Artificial intelligence · Particle swarm optimization algorithm

1 Introduction

The next new communication network will be an intelligent network with multi services, multi access technology and multi-level coverage. Among them, the application of multiple antennas [1] has great prospects and even necessary directions. The influence of deep fading can be alleviated effectively by MIMO technology through spatial diversity. The reliability of the communication system can be increased. Meanwhile, space division multiple access can be realized by adaptively adjusting weighting vector of antenna array. Finally, the space multiplexing or space diversity of communication system is realized, and the capacity of wireless link is greatly improved.

Artificial intelligence to minimize human intervention has been begun to explore in the management network [2], and a research group called intelligent definition network has also been launched to study the application of machine learning in the communication network. In addition, some EU 5g PPP projects, namely selfnet [3] and cognet [4], focus on the design and implementation of 5g mobile network intelligent management. The self net framework [5] utilizes self-organizing network (son) [6] and AI to automate infrastructure management based on Software Defined Network (SDN) [7] and network function Virtualization (nfv) [8].

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In reference [9], a test-bed is established to evaluate the performance that can be achieved in the real wireless scene, and the setting, closed-loop control and enabling algorithm of a 5g test-bed compatible with mobile edge computing are adopted. Taking traffic congestion as an example, the detection accuracy of traffic congestion rate was observed. The experimental results show that the application of artificial intelligence is feasible and effective. In reference [10], the basic concept of AI is introduced, and the relationship between AI and candidate technology in 5g cellular network is discussed. The effectiveness of artificial intelligence management and arrangement of cellular network resources is demonstrated. Reference [11] introduces the advantages of machine learning in artificial intelligence assisted wireless system and discusses their applications in the context of next generation network, including large-scale array antenna, cognitive radio, heterogeneous network, Pico/small base station, D2D network, etc. The types of supervised, unsupervised and reinforcement learning tools, the corresponding modeling methods and possible future applications in 5g networks are studied.

In this paper, by studying the anti-jamming strategy of multibeam decision-making system and the coordination and cooperation between multi-user devices, a multi antenna anti-jamming model based on artificial intelligence algorithm is established, with rules set, strategies used and expected return function. After the establishment of multi antenna anti-jamming model based on artificial intelligence algorithm, the model needs to be trained to verify whether the model is reasonable, whether it meets the needs of multi antenna system anti-jamming, and whether the training results can eventually converge. PSO algorithm is adopted to train artificial intelligence model to verify the rationality, convergence ability and performance of the model. Finally, the antenna array will form a great gain in the desired direction to improve the desired signal, while it will form a zero notch at the interference direction for interference suppression. It improves the SINR (signal to interference ratio) of the receiver effectively, and then improves the system performance and increase the system capacity.

2 System Model

It is assumed that there are a A users in the multi antenna communication system, and the number of antenna arrays at the transmitter and the receiver is m. All users are evenly distributed in the cell. Figure 1 is the system model.

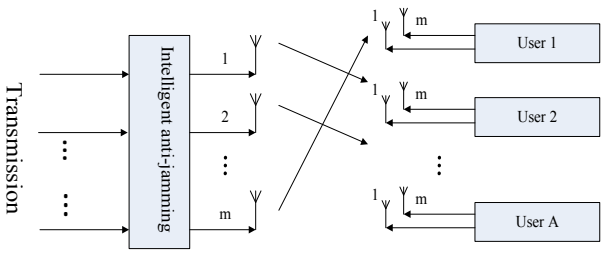

Fig. 1. Model diagram of multi antenna system

Then the received signal of the user l can be expressed as:

$$\mathbf{y} = \mathbf{H}_l \mathbf{v}_l \mathbf{x}_l + \mathbf{n} \tag{1}$$

Where $\mathbf{x}_l$ is the transmitted signal, assuming that the signal is a generalized stationary signal and $E\{x_l x_i^H\} = \begin{cases} 1 & l = i \\ 0 & l \neq i \end{cases}$. $\mathbf{H}_l$ Represents the channel matrix, assuming that the transmitter has perfectly known the channel information of the user. Indicates $\mathbf{v}_l$ the transmission weight, $\|\mathbf{v}_l\| = 1$. For white Gaussian noise vector $\mathbf{n}$, we assume $E[\mathbf{n}\mathbf{n}^H] = \mathbf{I}$. Then the SINR of the user l can be expressed as:

$$\mathbf{\Gamma}_l = \frac{\mathbf{v}_l^H \mathbf{R}_l \mathbf{v}_l}{\sum\limits_{i=1, i \neq l}^{L} \mathbf{v}_i^H \mathbf{R}_l \mathbf{v}_i + 1} \tag{2}$$

$\mathbf{v}_i$ represents the transmission weight of other users. $\mathbf{R}_l$ is the covariance matrix of the channel, which can be expressed as:

$$\mathbf{R}_l = E\{\mathbf{H}\mathbf{H}^H\} \tag{3}$$

The transmission weight $\mathbf{v}_l$ consists of two parts:

$$\mathbf{v}_l = \sqrt{P_l}\mathbf{u}_l \tag{4}$$

Then the SINR of the user l is a function of the user's transmission power P_l, namely:

$$\mathbf{\Gamma}_l(P_l) = \frac{P_l \mathbf{u}_l^H \mathbf{R}_l \mathbf{u}_l}{\sum\limits_{i=1, i \neq l}^{L} P_i \mathbf{u}_i^H \mathbf{R}_l \mathbf{u}_i + 1} \tag{5}$$

3 Multi Antenna Anti-jamming Algorithm Based on Artificial Intelligence Algorithm

3.1 Multi Antenna Anti-jamming Model Based on Artificial Intelligence Algorithm

The multi antenna anti-jamming model based on artificial intelligence algorithm consists of four parts: agents participating in decision-making, rule setting, strategies used and expected benefits. In the multi antenna anti-jamming model based on artificial intelligence algorithm in this paper, Different user devices are the agents involved in decision-making. Rule setting is the multi beam anti-jamming between multi-user devices. The set of strategies they adopt is their own transmitting power

$S_l = \{P_l, l = 1, 2, \cdots, L\}$. Each agent is independent and their strategies will affect other agent. The net utility function is:

$$U_l = U_u - U_c \tag{6}$$

U_u is the utility function of the user, which represents the benefits obtained by the user. U_c is the cost function of the user.

The utility function is defined as:

$$U_u = f(\Gamma_l) = \frac{\Gamma_l}{\Gamma_l + \alpha} \tag{7}$$

α is a constant, which is the same for all users.

The cost function U_c is:

$$U_c = \lambda P_l \tag{8}$$

λ is a constant, cost factor, which defines the user's cost when disturbed. So the net utility function is:

$$U_l = U_u - U_c = \frac{\Gamma_l}{\Gamma_l + \alpha} - \lambda P_l \tag{9}$$

From Eq. (9), it can be seen that the utility function U_l is a function expressed by the user's transmission power. The core of multi antenna anti-jamming model based on artificial intelligence algorithm in this paper is to maximize the net utility function, namely:

$$\arg\max U_l = \arg\max\left(\frac{\Gamma_l}{\Gamma_l + \alpha} - \lambda P_l\right) \tag{10}$$

3.2 Artificial Intelligence Training Model Based on Particle Swarm Optimization

After the establishment of multi antenna anti-jamming model based on artificial intelligence algorithm, the model needs to be trained to verify whether the model is reasonable, whether it meets the needs of multi antenna system anti-jamming, and whether the training results can eventually converge. In this paper, PSO algorithm is adopted to train the artificial intelligence model to verify the rationality, convergence ability and performance of the model.

The main idea is to operate according to the fitness value of individual (particle). Every user is thought as a particle without weight and volume in the n-dimensional search space, and a particle without weight and volume in the search space flies at a certain speed in the search space. Individual flight experience and group flight experience can help us to adjust the flight speed.

PSO algorithm is simple in concept, which is fast in search speed and wide in search range. At the same time, it has profound intelligent background, which is suitable for both scientific research and engineering application.

4 Results and Discussion

In this paper, a new anti-jamming algorithm based on artificial intelligence technology is proposed for multi antenna system with the aid of beamforming technology. A multi antenna anti-jamming model based on artificial intelligence algorithm is constructed. PSO algorithm is adopted to train artificial intelligence model to verify the rationality, convergence ability and performance of the model. Finally, the antenna array will form a great gain in the desired direction to improve the desired signal, while it will form a zero notch at the interference direction for interference suppression. It improves the SINR (signal to interference ratio) of the receiver effectively, and then improves the system performance and increase the system capacity.

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