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MACHINE LEARNING APPROACHES FOR CHANNEL ESTIMATION IN MIMO SYSTEMS

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Abstract

Multi-input multi-output (MIMO) systems have been researched for wireless networks to boost transmission reliability. However, one of the main issues that need to be addressed for optimal information transfer in MIMO is channel estimation. Though viable techniques for estimation are being presented, more investigation needs to be undertaken to boost estimation precision. Thus, for accurate channel estimation, this research introduces an innovative machine learning (ML) approach called bacterial foraging search-joint boosted recurrent network (BFS-BRN). Initially, every pilot block's channel outputs are computed with the least square channel estimator. Subsequently, the recommended BFS-BRN algorithm is trained to forecast the present channel response. The BFS optimization technique is used to maximize the functionality of the BRN. By adjusting the duration of the pilot series and the number of antennas, the suggested channel estimation scheme effectiveness is evaluated to figure out the measures such as mean squared error and bit-error-rate (BER and MSE). The suggested BFS-BRN scheme's complexity assessment is compared with previous methods.

Keywords- Machine learning (ML), transmission reliability, channel estimation, bacterial foraging search-joint boosted recurrent network (BFS-BRN), multiple-input multiple-output (MIMO)

1. Introduction

The fundamental essentials of wireless communication that enhance data rates, range efficiency, and dependability are multiple-input multiple-output (MIMO) systems. MIMO addresses multipath loss and enables concurrent data to be removed by using spatial range via several antennas for communication and response [1]. However, a precise channel estimate is essential to fully recognize the promise of MIMO, which presents a difficulty in dynamic wireless conditions. Estimating channel parameters from conventional signals is known as control evaluation, and it is a fundamental step in organization optimization [2]. Machine learning (ML) has succeeded in pilot-based techniques, which fix latency, mobility, and dynamic channel problems in MIMO systems [3]. ML presents an adaptive solution for MIMO control prediction by successfully capturing spatial and temporal correlations [4]. There are performance drawbacks when MIMO channel evaluation is used with a big antenna [5]. Improving channel estimate methods for MIMO systems is the objective of this research. This entails creating reliable algorithms to precisely predict channel properties, enhancing signal delivery, and reducing interference to enhance system dependability and performance in wireless communication environments. Subsequently, the recommended BFS-BRN algorithm is trained to forecast the present channel response.

2. Related Work

The article [6] suggested an approach for IRS-assisted MIMO communication system channel estimation. They proposed two methods an iterative alternating estimation scheme and a closed-form solution for rank-1 matrix approximation based on Khatri-Rao factorization. The research [7] explored that due to sparse Bayesian learning and iterative likelihood maximization, challenges in predicting millimeter wave (mmWave) MIMO channels arising from few chains and huge matrices are overcome. The study [8] described a method for creating an analog-to-digital converter (ADC) that is 1 bit. The study proposed a two-step multi-user joint channel estimation approach. The article [9] explored the reconfigurable intelligent surface-base station (RIS-BS) shared channel, using common column-block sparsity for received signals and row-block sparsity.The article [10] introduced a multi-step approach. Its low signal-to-noise ratio (SNR) beam-formed channel and carrier frequency offset (CFO) is originally estimated using ML criteria via transmitter-receiver training. The high-dimensional MIMO channel is estimated using angular sparsity, demonstrating a minimal overhead and encouraging efficiency.

3. Methodology

This study presents an innovative ML approach called BFS-BRN, which combines BRN with bacterial foraging search to improve channel estimation. The channel outputs for every Pilot block are first calculated using the least squares channel estimator. After that, to maximize BRN performance, BFS optimization is used to train the BFS-BRN model to anticipate the current channel response.

3.1 MIMO system

A MIMO system improves communication and control efficiency by concurrently using multiple input signals and producing numerous output signals. Utilizing spatial diversity to increase data throughput, system dependability, and wavelength efficiency, MIMO is revolutionizing current wireless technology and finds applications in wireless communication, robotics, and radar systems.

3.2 System model

Transmitting pilot sequences and getting feedback is essential for effective channel state information (CSI) estimation in MIMO communication settings with t transmitters and r receivers. Generated and received signals are required for CSI estimation expressed as in equation (1).

$$z_n = G_{o_n} + Y_n \quad (1)$$

The received signal, o_n, can be expressed as o_n. When G is used for pilot training, pilot sequences are provided in equation (2).

$$Z = \mathrm{GO} + \mathrm{Y} \quad (2)$$

The channel estimator finds G based on Y_n.

3.3 Channel model

The study simulates a multiple signal route channel between the transmitter and receiver. The suggested method, which makes use of BFS-BRN, provides dependable packet transmission without exact Doppler rate calculation. Equation (3) defines the fading channel that varies in time between t and $r$at z.

$$N(z) = \begin{matrix} n_{11}(z) n_{12}(z) \ldots n_{1q}(z) \\ n_{21}(z) n_{22}(z) \ldots n_{2q}(z) \\ \vdots \quad \vdots \quad \cdots \quad \vdots \\ n_{s1}(z) n_{s2}(z) \cdots n_{sq}(z) \end{matrix} \quad (3)$$

At time$n_{sq}(z)$, t^{th} transmitter and r^{th} receiver. The received signal probability is defined by the probability density function (PDF) of the Rayleigh fading channel expressed as in equation (4).

$$o(q_0) = \frac{q_0}{\sigma^2} \exp\left(-\frac{q_0^2}{2\sigma^2}\right) \quad (4)$$

Equation (5) is a received signal's amplitude,σ^2 variance, and $2\sigma^2$multipath signal strength are shown by q_0. Defined PDF of SNR instantaneously.

$$o(\gamma_a) = \frac{1}{\bar{\gamma}_a} f^{\frac{-\bar{\gamma}_a}{\bar{\gamma}_a}} \quad (5)$$

3.4 Pilot sequence channel response

The channel estimate is used to predict the current control reaction based on past pilot sequence data. To predict the present pilot sequence channel response, a BFS-BRN model is used (G_l) based on the channel response from the prior pilot sequence, which is represented as G_{l-1} following equation (6).

$$G_{l-1} = (O)^{-1} Z \quad (6)$$

3.5 Channel estimation using bacterial foraging search-joint boosted recurrent network (BFS-BRN)

BFS-BRN improves communication systems performance via adaptive optimization in complicated settings by using BFS-BRN for effective channel estimation.

3.5.1Boosted recurrent network (BRN)

Channel estimation is essential for dependable communication in MIMO systems. Recurrent neural networks (RNNs) with boosting methods are used by Boosted Recurrent Networks (BRNs) to improve this process. The intricate interactions inside the channel are adaptively learned by BRNs, increasing the accuracy of the estimate. BRNs improve performance in a variety of channel situations by identifying temporal dependencies and improving their predictions via repeated training. By offering reliable and effective channel estimates, this method improves MIMO system dependability. Algorithm 1 shows the procedure of BRN.

Algorithm 1: Procedure of BRN

Establish the example weights at zero: $C_1(r) = 1/R$the number of training examples. Put the iteration counter at 0: $m = 0$
Iterate
(a) Increment m. Learn with a BRN$g_m$by using the entire training set and by weighting the squared error computed for example r with $C_m(r)$, the weight of example r for the iteration m ;
(b) Update the weights of the examples:

(i) Compute$K_m(r)$Regarding each r = 1, ", R according towards a decrease in the equation (7 to 10):

$$K_m^{linear}(r) = \frac{\left|z_r^{(m)}(w_r)-z_r\right|}{T_m},\ K_m^{quadratic}(r) = \frac{\left|z_r^{(m)}(w_r)-z_r\right|^2}{T_m^2} \quad (7)$$

$$K_m^{\text{exponential}}(r) = 1 - \exp(-\left|z_r^{(m)}(w_r) - z_r\right|T_m)\text{with}$$

$$T_m = \sup_r \left|z_r^{(m)}(w_r) - z_r\right|; \quad (8)$$

(ii) Compute$\varepsilon_m = \sum_{r=1}^{R} C_m(r)K_m(r)$ and $\alpha_m = \frac{1-\varepsilon_m}{\varepsilon_m}$; (9)

$$C_{m+1}(r) = \frac{1+l.o_{m+1}(r)}{R+l} with O_{m+1}(r) = \frac{C_m(r)\alpha_m^{(K_m(r)-1)}}{Y_m}\text{until}\varepsilon_m < 0.5 \quad (10)$$

Combine BRN by using the weighted median

3.5.2 Bacterial foraging search (BFS)

By performing bacterial behavior, bacterial foraging search maximizes channel estimate for strong signal reception.

3.5.2.1 Chemotaxis

Bio-inspired systems are used in channel estimation in MIMO systems with chemotaxis to optimize system performance in wireless communications by improving signal reception and adaptively tweaking parameters as in equation (11).

$$\theta^j(a,f,o) + D(q)\frac{\Delta(q)}{\sqrt{\Delta^z(q)\Delta(q)}} = \theta^q(a+1,f,o) \quad (11)$$

$\Delta(q)$is a strange integer in $[-1, 1]$ during channel MIMO. Based on run or tumble activity, the fitness of each chemotactic step, a, f, o, is evaluated.

3.5.2.2 Reproduction

Channel estimate in MIMO networks based on recurrence is repeatedly improved by recreating pilot signals and modifying parameters to improve performance and accuracy.

3.5.2.3 Elimination and Dispersal

In MIMO systems, channel estimation via dispersion and elimination entails dispersing pilot symbols among antennas and eliminating interference to refine estimates for precise retrieval of spatial information.

4. Result and discussion

The suggested techniques, BFS-BRN is used for channel estimation in MIMO Systems, which includes several concert indicators utilized to assess the BIT and MSE of the BFS-BRN technique is compared to other existing techniques, such as space-time block coding (STBC) [11] and space-frequency block coding (SFBC) [11].

4.1 Bit Error Rate (BER)

With MIMO systems, channel estimation lowers BER by approximating channel properties like interference and fading. It improves signal reception, which results in better BER performance in multi-antenna communication setups, by using strategies like pilot signals and algorithms like Least Squares or Minimum MSE. The BER measures the ratio of erroneous or modified bits to all bits sent in a certain time frame. Examined about SNR, BER reduces in Figure 1 with increasing SNR, suggesting better results from all approaches. As a result, channel estimation using the suggested BFS-BRN approach has lower performance of BER, compared to the existing techniques.

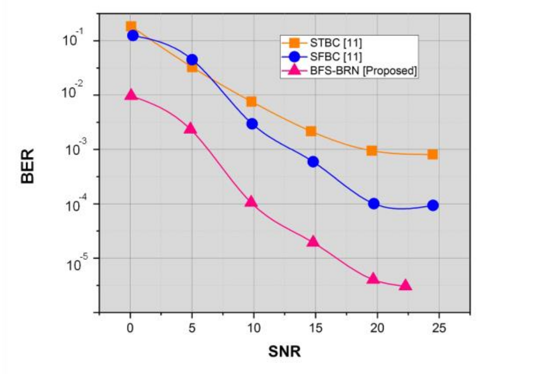

Figure 1: BER vs. SNR

4.2 Mean Squared Error (MSE)

In MIMO systems, the accuracy of actual channel responses is assessed using the MSE channel estimate measure. By averaging the squared differences between each channel coefficient, estimate quality is measured. In multi-antenna communication systems, a lower MSE indicates better estimation performance, which is essential for dependable data transfer. Its relationship with SNR a metric that quantifies the communication's power-to-noise power ratio is investigated. SNR, which is usually measured in dB, affects MSE performance. As shown in Figure 2, MSE falls as SNR increases for all approaches. In contrast to the existing and suggested approaches, the recommended BFS-BRN technique has a lesser MSE.

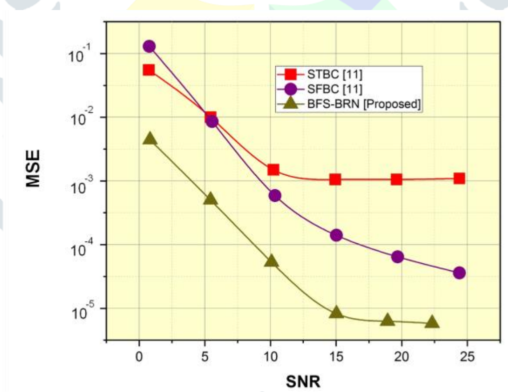

Figure 2: MSE vs. SNR

5. Conclusion

The study concludes by suggesting BFS-BRN, a revolutionary ML technique, to improve channel estimates in MIMO systems. Through the integration of BRN and bacterial foraging search, the technique improves wireless communication accuracy and dependability. Its excellent performance in terms of BER and MSE when compared to previous methodologies highlights its potential for transmission optimization in complicated circumstances. The technical needs and complexity of the BFS-BRN implementation are among its limitations. Following studies endeavors can delve into specific deployment challenges and modify the methodology according to dynamic channel settings.

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