OPTIMIZING MODULATION RECOGNITION IN MIMO-OFDM SYSTEMS USING SPARROW SEARCH OPTIMIZATION (SSO) AND DEEP LEARNING (DL) MODELS

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Abstract:

With the rapid advancement of wireless communication systems, the need for efficient and reliable Automatic Modulation Recognition (AMR) has become essential, especially for MIMO-OFDM systems used in modern wireless technologies. The complexity of recognizing modulation schemes in MIMO-OFDM systems is further heightened by the challenges of signal interference, noise, and the dynamic nature of the communication channels. This paper proposes a novel approach combining the Sparrow Search Optimization (SSO) algorithm with ensemble deep learning (DL) models to improve the performance of AMR in MIMO-OFDM systems. The proposed Sparrow Search Optimization with Ensemble Learning-based Automated Modulation Recognition and Classification (SSOEL-AMRC) technique utilizes three DL models: Stacked Autoencoder (SAE), Long Short-Term Memory (LSTM), and Recurrent Neural Network (RNN) to classify modulation types. The SSO algorithm optimizes the hyperparameters of these models, thereby enhancing the overall recognition accuracy and robustness of the system. Simulation results show that the proposed method significantly outperforms traditional methods, such as feature-based and likelihood-based approaches, by achieving higher classification accuracy, better computational efficiency, and increased resilience to noise and interference. The study concludes that the SSOEL-AMRC technique offers a promising solution for the next-generation MIMO-OFDM systems, especially in cognitive radio applications, where dynamic spectrum management and efficient modulation recognition are crucial.

Keywords: MIMO-OFDM, Automatic Modulation Recognition (AMR), Sparrow Search Optimization (SSO), Deep Learning (DL), Ensemble Learning, Stacked Autoencoder (SAE).

INTRODUCTION

Cognitive radio is a wireless transmission network which addresses the ineffectiveness of radio resource usage through computational intelligence as well as have both military and civilian applications. The classification of modulation format of unknown received signal is the major task in Cognitive radio (Khan et al. 2023). As the fusion of OFDMdata modulation and multiple-antenna (MIMO) transmission becomes vital to fifth generation (5G) and fourth generation (4G) wireless technologies, a need has arisen for developing the classification techniques capable of dealing with MIMOOFDM signals (Liang et al. 2022). In MIMO-OFDM system, different modulation systems are used for transmitting the data over various subcarriers and antennas (Silpa et al. 2023). The choice of modulation scheme depends on the specific needs of the MIMO-OFDM system namely desired data rate, channel condition, trade-off, and available bandwidth between error performance and spectral efficiency and depends on factors like spectral efficiency, system requirements, and channel conditions (Li et al. 2021). Various modulation systems can be employed for multiple subcarriers or in combination to improve performance of the overall system.

Automatic Modulation Recognition (AMR) is an intermediary stage between signal demodulation and detection (Nair et al. 2022). This method is capable of identifying the types of signal modulation and thereby attaining the data in the signal without knowing the system parameter. After decades of development o f AMR technique, its classical detection techniques could be divided into feature-based and likelihood-based methods (Zheng et al. 2023). Feature based method requires manual feature extraction, which makes the detection outcomes greatly rely on expert knowledge of feature extraction (Mahmood et al. 2021), whereas Likelihood-based method has theoretical optimality, but the computational cost is high. Hence, these two detection techniques are not suited for more complex transmission systems (Song et al. 2023). In recent times, researcher workers in the communication field have exploited standard network in deep learning (DL) namely RNN, CNN and so on (Bai et al. 2020). AMR has shown that DL-based modulation detection algorithm performs better than classical modulation recognition approaches. This study proposes a Sparrow Search Optimization with Ensemble Learning-based Automated Modulation Recognition and Classification (SSOEL-AMRC) technique specifically designed for MIMO-OFDM systems. The SSOEL-AMRC technique combines the power of ensemble learning and DL models to accurately recognize and classify modulation signals. The proposed approach can be summarized as follows: Feature Extraction: The SSOEL-AMRC technique starts by extracting feature vectors from the input signals. Feature extraction plays a crucial role in capturing discriminative information from the signals. Various techniques can be employed for feature extraction, such as time-domain and frequency-domain analysis.

Ensemble of DL Models: Three DL models, namely Stacked

Autoencoder (SAE), Long Short-Term Memory (LSTM), and Recurrent Neural Network (RNN), are utilized for modulation recognition. Ensemble learning, which combines the predictions of multiple models, helps improve the classification accuracy and robustness. Sparrow Search Optimization (SSO): The SSO algorithm is employed to optimize the hyperparameters related to the DL models. SSO is a recently developed nature-inspired optimization algorithm based on the behavior of sparrows. It effectively searches the hyperparameter space to find the optimal configuration, leading to improved classification results. Training and Validation: The proposed SSOEL-AMRC technique is experimentally validated under various measures. The training dataset consists of labeled modulation signals, where the DL models are trained using backpropagation and gradient-based optimization algorithms. The validation dataset is then used to evaluate the performance of the trained models, considering metrics such as accuracy, precision, recall, and F1-score. Performance Evaluation: The performance of the SSOELAMRC technique is compared with traditional feature-based and likelihood-based methods as well as other DL-based approaches. The evaluation includes analyzing the classification accuracy, computational efficiency, and robustness against noise and interference.

Huynh-The et al. (2022) viable approach for MIMO-OFDM in the context of signal-to-noise ratio and unknown frequency-selective fading channels was proposed. The researcher employed a sophisticated neural network architecture, such as the 3D MIMO-OFDM-CNN, in order to investigate the modulation pattern derived from the received signals. In their recent study, Ge et al. (2021) developed a novel channel predictive framework that incorporates imperfect channel prediction within the deep neural network (DNN) methodology.

This approach replaces the traditional interpolation technique and achieves enhanced accuracy in channel prediction. Based on the examination of simulation results and algorithm performance, it can be concluded that the provided deep neural network (DNN) channel predictive technique exhibits superior performance compared to the classical least square approach in the context of imperfect channel prediction.

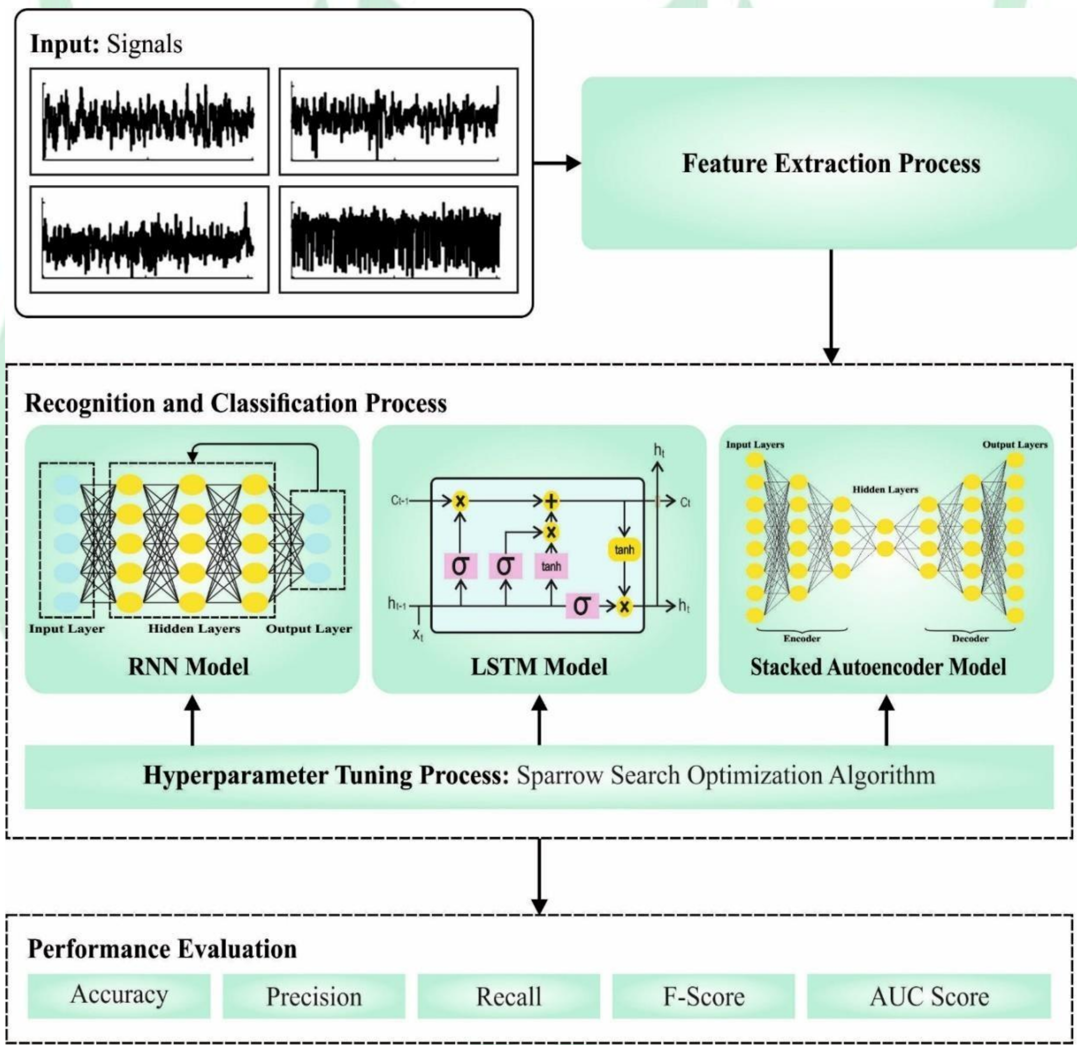
Yang & Chen (2022) presented a method that depends on DL for MIMO-OFDM System. In this presented system, a receiver can be devised for eliminating successive interference cancellations related to DL for many users. The channel estimation and signal detection are conducted with the use of DNN that can be trained offline relies on simulation dataset. Moreover, the symbols online were recovered directly. Ro et al. (2022) introduce the MIMO recognition method with the use of the DNN related ensemble ML for maximum error performance in wireless transmission systems. For the MIMO recognition related to the ensemble ML, all learning approaches for the DNN are produced offline and the recognition can take place online utilizing already learned methods.

Zhou et al. (2021) present a model-driven DL-related detector for resolving this issue. The prototype of detector is

(OAMP) (orthogonal approximate message passing method) which can mitigate interference but includes matrix inversion with high complication. The author uses the conjugate gradient approach to minimalizing the computatio complexities of OAMP. Next, the detection performance can be enhanced by unfolding the revised method into network and learning the best values of its parameters,. Hamedani et al. (2020) present a MIMO-OFDM system, new energy effective spectrum sensing algorithm for multiple-input in dynamic spectrum sharing (DSS) environment. Specifically, a spiking reservoir computing (RC) related method was presented for spectrum sensing of presented systems to exploit the temporal and spatial correlation.

THE PROPOSED MODEL

This research primarily focuses on the development of the SSOELAMRC technique for identifying and classifying modulation signals within MIMO-OFDM systems. The SSOEL-AMRC technique employs ensemble of three DL models to accurately recognize the modulation signals. In the SSOEL-AMRC technique, three major processes are involved namely feature extraction, ensemble classification, and hyperparameter tuning. Figure 4.1 depicts the working procedure of SSOEL-AMRC method.



Working procedure of SSOEL-AMRC method

Feature Extraction

The process of feature extraction is dependent on the asymptotic Gaussian properties exhibited by multi-carrier signals. WPM and OFDM signals are examples of multi-carrier signals, wherein each subcarrier is mutually orthogonal. The amplitude distribution of a multi-carrier signal is commonly considered to approximate a Gaussian distribution with asymptotic Gaussian properties, as per the central limit theorem (CLT). Furthermore, the level of Gaussian characteristic has a correlation with the various subcarriers.

Conversely, the single-carrier signal lacks this characteristic and exhibits a Non-Gaussian distribution. The V_20 mixed order moment has been utilised to express the value in a multi-path channel, as follows:

$$\mathcal{V}_{20} = \frac{M_{4,2}(y)}{M_{2,1}^2(y)} = \frac{E(|a(i)|^4)}{E(|a(i)|^2)} \quad (4.5)$$

Ensemble Modulation Recognition

For modulation recognition, three DL models namely RNN, LSTM, and SAE are used. Recurrent Neural Network (RNN) constitutes a class of NN that expands the functionality of NN by maintaining the temporal dimension of time series (sequential dataset) (Essien et al. 2019). Unlike conventional FFNN, RNN adds a 'recurrent' or loop component for connecting the neuron with itself and unfolding it such that it is capable of making a probability distribution in the time series. RNN has hidden layer (HL) that is upgraded by the time series data derived from sequential data with output that is dependent on HL. Where U and V represent the weight of the HL and output layers correspondingly, while W denotes the transition weight of the HL.

Given that input vector x_τ at τ time, s_τ shows the HL of RNN at τ time that can be evaluated by the component-wise product of the input vector and the prior HL. Thus, the HL at τ time, given its prior h_{t-1} hidden state can be estimated as follows:

$$h_\tau = \sigma(W_{hx}x_t + W_{hh}h_{t-1} + b) \quad (4.6)$$

where W_{hx} symbolizes the weight between the recurrent hidden (HN) and input nodes, W_{hh} symbolizes the weight between the prior time step and the recurrent node of the HN itself, b and σ correspondingly denote bias and nonlinear (sigmoid) activation. LSTM reminds the common RNN structure and modifies the memory cell unit, which makes it capable of storing extended time interval. A forget, input, and output gates controlling the data flow within the memory cell:

$$I_t = \sigma(W_{IF}x_t + W_{hI}h_{t-1} + W_{CI}C_t + b_I)$$

$$O_t = \sigma(W_{xO}x_t + W_{hO}h_{t-1} + W_{CO}C_t + b_O) \quad (4.7)$$
$$F_t = \sigma(W_{xF}x_t + W_{hF}h_{t-1} + W_{CF}C_t + b_F)$$

whereas, W denotes the weight of recurrent connections (viz, W_{IF} specifies the weight of input-forget gates). In Eq. (4.7), F_t I_t, and O_t, characterize the forget, input, and output gate, correspondingly. σ refers to the sigmoid activation function. h represents the hidden state, and b denotes the bias. The memory C_t of this unit is attained using Eq. (4.8):

$$C_t = F_tC_{t-1} + I_t\tanh(W_{xC}x_t + W_{hC}h_{t-1} + b_C) \quad (4.8)$$

The output vector (hidden state vector) would be transported to the next time interval, and it is evaluated as follows:

$$h_t = O_t\tanh(C_t) \quad (4.9)$$

The SAE is a stack of AEs and, similar to AEs, which can be learned in an unsupervised fashion. In this work, the SAE is characterized by the Bidirectional 2D ConvLSTM architecture. The learning procedure includes layer-wise training to minimalize the error between output and input vectors. The activation function employed within the hidden unit is ReLU that can be arithmetically shown below.

$$g(z) = \max\{0, z\} \tag{4.10}$$

The succeeding layer of the AE is the HL of the prior one, with all the layers using optimization function that is the squared reconstructed error J of the AE layer defined as follows.

$$\text{argmin}_{W_1,b_1,W_2,b_2}(\text{J})$$
$$= \begin{matrix} argmin \\ W_1, b_1, W_2, b_2 \end{matrix} \left[\frac{\sum_{i=1}^{m} ||x_i - x_i'|| + J_{wd} + J_{sp}}{2} \right] \tag{4.11}$$

In Equation 4.(11),m shows the training dataset size, x_i and x_i' correspondingly characterize the i-th values of the input vector, J denotes the squared reconstructed error of the single AE layer.

Hyperparameter Tuning

Lastly, the SSO algorithm chooses the hyperparameters related to the DL models. SSO algorithm is a new bionic optimization technique (Song et al. 2023). The motivation comes from the anti-predator, foraging, and group intelligence behaviors of sparrow. Strong optimization ability and fast convergence speed are the benefits of SSO algorithm. In this work, the solution of optimization problem can be attained by imitating the sparrow foraging method that involves predators, discoverer sparrows, and follower sparrows.

In all the iterations, the discoverer position can be updated using Equation (4.12):

$$X_{i,j}^{t+1} = \begin{cases} X_{i,j}^{t} * \exp\left(\frac{-i}{\alpha * iier_{\max}}\right) & if\ R_2 < ST \\ X_{i,j}^{t} + Q * L & if\ R_2 \geq ST \end{cases} \tag{4.12}$$

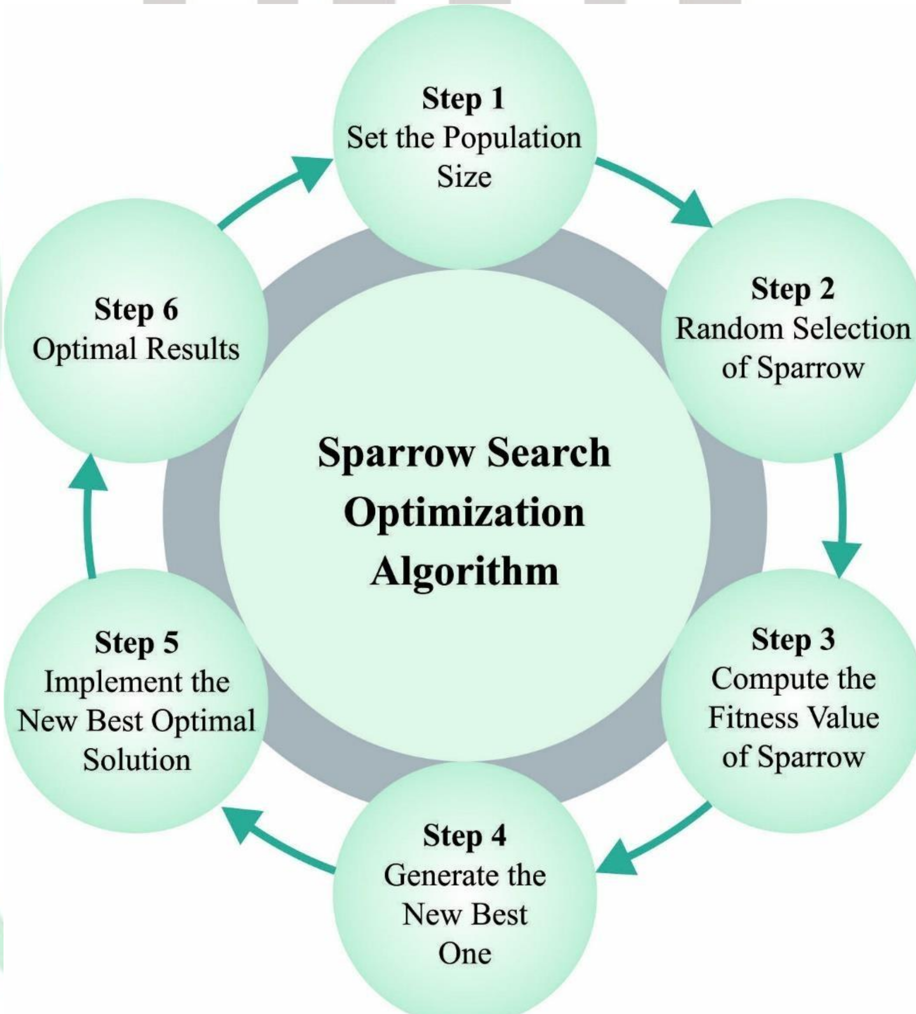
where $X_{i,j}$ indicates the location of i^{th} sparrow at j^{th} dimension, t represents the amount of iterations and $iter_{\max}$ shows a constant with the maximum amount of iterations. α is a randomly generated integer, $\alpha \in (0,1)$. R_2 and ST represents the alarm value and the safety threshold, correspondingly, $(R_2 \in (0,1\ (ST \in (0.5,1.0))$. Q denotes the random value that follows normal distribution. L represents the matrix that all the component inside is 1.

If $R_2 < ST$, then there is no predator around the foraging location, and the discoverer carries out a large number of search processes. If $R_2 \geq ST$, it implies that sparrow has found predator and sent alarm to other members of the group. Each individual should quickly fly towards another safer region for foraging.

The location updating of the follower can be given as follows:

$$X_{i,j}^{t+1} = \begin{cases} Q * \exp\left(\frac{x_{worst}^{t} - x_{i,j}^{t}}{i^2}\right) & if\ i > n/2 \\ X_P^{t+1} + \left|X_{i,j}^{t} - X_P^{t+1}\right| * A^{+} * L & otherwise \end{cases} \quad (4.13)$$

In Equation (4.13), X_P shows the optimum location occupied by the discoverer. X_{worsi} represents the existing worst location. n denotes the number of sparrow population. A indicates a matrix that every component inside is arbitrarily allotted 1 or -1, and $A^{+} = A^{T}(AA^{T})^{-1}$. Figure 4.2 represents the steps included in SSO approach.



Steps included in SSO

Once the sparrow population realizes the danger, it makes anti-predation behaviors which can be mathematically formulated as follows:

$$X_{i,j}^{t+1} = \begin{cases} X_{best}^{t} + \beta * \left|X_{i,j}^{t} - X_{best}^{t}\right| & if\ f_i > f_g \\ X_{i,j}^{t} + K * \left(\frac{\left|X_{i,i}^{t} - X_{worst}^{t}\right|}{(f_i - f_w) + \varepsilon}\right) & if\ f_i = f_g \end{cases} \quad (\mathbf{4}.14)$$

In Equation (4.14), X_{best} shows the present optimum position. β denotes the random variable that follows the standard distribution. K denotes a random integer, $K \in (-1,1)$. f_i shows the fitness value of the existing sparrow f_g represents the present optimum fitness value, and f_w denotes the existing worst fitness value. The fitness value is evaluated by RMSE of predicted and original dam datasets. ε shows the smaller constant to avoid the denominator being zero.

The individual sparrow update the position based on Equations (4.12)-(4.14) until the maximal amount of iterations is obtained, and the global optimum parameter can be defined where the sparrow has the maximum fitness value.

Fitness selection is a key factor in the SSO method. Solution encoding is exploited for evaluating the goodness of solution candidate. Here, the accuracy value is the primary condition exploited for designing a fitness function.

$$Fitness = \max(P) \tag{4.15}$$

$$P = \frac{TP}{TP + FP} \tag{4.16}$$

where TP represent the true positive and FP symbolizes the false positive value.

Conclusion

The proposed SSOEL-AMRC model effectively enhances modulation recognition performance in MIMO-OFDM systems by integrating Sparrow Search Optimization (SSO) with an ensemble of deep learning architectures, including SAE, LSTM, and RNN. Through optimized hyperparameter selection and robust feature extraction based on multi-carrier Gaussian properties, the system demonstrates superior accuracy, noise tolerance, and classification reliability compared to traditional feature-based and likelihood-based AMR methods. The SSO algorithm's strong global search capability significantly improves model convergence and recognition stability, particularly under challenging fading and interference conditions. Overall, the SSOEL-AMRC framework offers a powerful and scalable solution for next-generation wireless systems and cognitive radio networks, enabling more intelligent spectrum utilization and resilient modulation classification.

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