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PAPERS

Convolutional fuzzy neural network based symbol detection in MIMO NOMA systems

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One of the most important tasks to be considered in wireless communication systems, especially in multi-carrier systems such as Multi-Input Multi Output Non-Orthogonal (MIMO-NOMA), is to correctly estimate the channel state information for coherent detection at the receiver. A hybrid deep learning model, called convolutional fuzzy deep neural networks, is proposed in this study for accurately estimating channel state information and detecting symbols in MIMO-NOMA systems. The performance of this proposal has been compared to traditional algorithms like Least Square Error- Successive Interference Cancelation (LS-SIC) and linear minimum mean square (LMMSE-SIC), as well as to other deep learning methods such as convolutional neural networks. With this proposed scheme, significantly less bit error rate is obtained in both Rician and Rayleigh channel environment compared to other algorithms. In addition to the high performance of this scheme, the fact that it does not need channel statistics is another important advantage.

K e y w o r d s: MIMO-NOMA, channel estimation, symbol detection, convolutional fuzzy neural network

1 Introduction

The growing demand for high data rate internet, streaming services, and data-intensive applications has led to the development of various technologies and techniques for achieving high data rates. The limited available frequency band is one of the biggest obstacles to high-rate data transmission. In order to overcome this obstacle, multi-carrier systems are used that provide spectral efficiency and, as a result, high data rate transmission by using the bandwidth in the most efficient way. Multiple user data is multiplexed in the code or power domain utilizing the same time and frequency resources in the NOMA technology, which is one of the multi-carrier systems and also forms the backbone of 5G mobile communication. Spectral efficiency, multi-user support, lower latency and quality of service (QoS) are the most important advantages of NOMA [1,2]. In addition, MIMO-NOMA, which is obtained by combining the NOMA system with the multi-antenna structure, will not only increase the resistance of the system to the effects of multipath fading, but also provide less power consumption, reduced bit errors and a remarkable capacity increase [3]. To detect the signals of each user at the receiver in the multi-user NOMA approach, a traditional method SIC is employed. In the SIC method, the user signal with the strongest signal value is extracted first from the total signals of different users transmitted at the same time and frequency domain, and this process is repeated until the signal of the lowest power user. However, if the number of users in the system is high, the complexity and energy usage of the receiver will increase, and if any of the users has an error in the signal detection, the other users' signals will also be incorrectly detected. The number of users in the system will be reduced as a result of this.

One of the primary issues in NOMA systems is precisely estimating the channel state information (CSI) of the users for coherent symbol detection. The process of estimating the parameters of the communication channel between the receiver and the transmitter is known as channel estimation. This information is crucial for the receiver to decode the transmitted signal correctly. There are various techniques used for channel estimation in NOMA systems, each with their own advantages and disadvantages. Some of the most commonly used techniques include pilot-based estimation such as MMSE and LS techniques. These techniques are of great importance in NOMA systems as they enable the receiver to accurately decode the superimposed signals and thus improve the overall system performance. The LS method estimates CSI by reducing the sum of squared error between the received and transmitted signals. It is a linear estimator that assumes that the channel is time-invariant and that the noise is white and Gaussian. MMSE channel estimation is an improvement over LS channel estimation, as it accounts for the effect of noise on the channel estimation. It estimates the CSI by minimizing MSE between the received and transmitted signals while also considering noise power and channel correlation. Since the MMSE algorithm needs statistical data of the channel, which is difficult to obtain in real-time transmission, it is not possible to use this algorithm practically. Since the MMSE algorithm needs statistical data of the channel, which is difficult to obtain in real-time transmission, it is not possible to use this algorithm practically. Although the LS algorithm is easy to use, the inadequacy of the performance

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of this algorithm in fading channels limits the usability of this algorithm. [4]

Recently, there has been a considerable increase in interest in employing deep learning neural networks to solve these issues. The most important advantages of deep learning neural networks are their learning capabilities, flexible solutions in solving nonlinear problems, easing the hardware load by using few parameters, and parallel processing capabilities. To address the issues of channel estimation and symbol detection for wireless communication platform, many types of deep learning neural networks have been proposed in the literature [4-13]. For instance, in [5], the performance of the signal detector created with convolutional neural networks has been compared with the SIC and then better symbol error rate was obtained. In the studies [6 -8], deep learning neural networks has showed a better BER performance than LS and MMSE methods. In [9], convolutional neural network (CNN) -based deep learning methods have been used to reduce the mean square error to estimate the CSI in MIMO systems in transmission state in time varying channels and quasi-static fading channels. In addition, in [10], long short-time deep learning, which is a kind of deep learning for OFDM systems, has been proposed. Another application of the deep learning neural networks in symbol detection is the work done in [11] for NOMA systems. Deep learning-based channel estimators also perform well over various channel environments. In order to evaluate their performances over realistic and fading channels, the transmission states have been examined in [12] for the real mobile transmission channel, and in [13] for the frequency selective channels respectively. It is clear from these studies that deep learning neural networks have an effective solution for symbol detection in multi-carrier systems and have achieved a remarkable performance improvement over classical technique.

The deep neuro fuzzy technique, which was developed by integrating CNN with fuzzy systems, has been proposed in recent years and has increased approximation function and system performance while handling nonlinear issues compared to convolutional neural networks [14-19]. Deep convolutional fuzzy neural (CFNN) network has started to be used effectively to solve many problems such as classification and image processing. For example, emotional classification was performed from multimodal audio, text and video data with CFNN networks created by combining fuzzy logic and convolutional neural networks, and successful results were obtained in the study in [17]. Also in the study in [18], the proposed fuzzy convolutional neural networks provided an increase in performance compared to classical methods in the sentiment classification task problem.

This study presents the use of CFNN for symbol detection in MIMO-NOMA and demonstrates a significant improvement in performance when compared to the CNN and traditional methods found in the literature. To the best of our knowledge, it is the first time that the CFFN that is used for symbol detection. In addition, another advantage of the proposed method is that it does not need any statistical data of the channel.

2 MIMO-NOMA system model

For a multi-user MIMO- NOMA with M receiver and N transmitter antennas transmitted signal from base station can be represented as

$$\boldsymbol{T} = \boldsymbol{P}\mathbf{x}, \tag{1}$$

where $\boldsymbol{P}$ represent the $N \times N$ precoding matrix and $N \times 1$ information vector symbol vector $\mathbf{x}$ can be given as

$$\mathbf{x} = \begin{bmatrix} x_{1,1}\sqrt{P_{\max}\eta_{1,1}} + \cdots + x_{1,i}\sqrt{P_{\max}\eta_{1,i}} \\ \vdots \\ x_{n,1}\sqrt{P_{\max}\eta_{n,1}} + \cdots + x_{n,i}\sqrt{P_{\max}\eta_{n,i}} \end{bmatrix}, \tag{2}$$

where $\eta_{n,k}$ is power allocation coefficient and $x_{n,k}$ is information signal for $i-th$ user in the $n-th$ cluster. Then the observed signal can be written as

$$\boldsymbol{y}_{n,i} = \boldsymbol{H}_{n,i}\boldsymbol{P}\mathbf{x} + \boldsymbol{N}_{n,i}, \tag{3}$$

where $\boldsymbol{N}_{n,1}$ denotes white Gaussian noise (independent, identically distributed) and $\boldsymbol{H}_{n,1}$ is the channel matrix between $i-th$ user in the $n-th$ cluster and BS. In case of detection vector $\mathbf{r}_{n,1}^{H}$ is applied, the observed signal can be represented as

$$\begin{aligned} \mathbf{r}_{n,i}^{H}\boldsymbol{y}_{n,i} &= \mathbf{r}_{n,i}^{H}\boldsymbol{H}_{n,i}p_n\sum_{i=1}^{K} x_{n,i}\sqrt{P_{\max}\eta_{n,i}} + \\ &+ \underbrace{\sum_{l=1,l\neq n}^{N} \mathbf{r}_{n,i}^{H}\boldsymbol{H}_{n,i}p_l x_l}_{\text{(Intra and inter)cluster interference}} + \mathbf{r}_{n,i}^{H}\boldsymbol{N}_{n,i}, \end{aligned} \tag{4}$$

where x_l is the k-th row of $\mathbf{x}$ Then the signal can be simplified as

$$\mathbf{r}_{n,i}^{H}\boldsymbol{y}_{n,i} = \mathbf{r}_{n,i}^{H}\boldsymbol{H}_{n,i}p_n\sum_{i=1}^{K} x_{n,i}\sqrt{P_{\max}\eta_{n,i}} + . \tag{5}$$

Here $(.)^{H}$ is the Hermitian transpose, [1-3].

3 Convolutional fuzzy neural network for symbol detection

CFNN is a type of deep learning method that combines the ideas of fuzzy logic and CNN. In CFNN, features are extracted from the input data by a convolutional layer and processed by a fuzzy layer. Each feature is assigned a membership degree by the fuzzy layer, which represents the degree to which it belongs to a certain class or category. This allows the network to handle imprecise or uncertain data, making it well-suited for tasks in

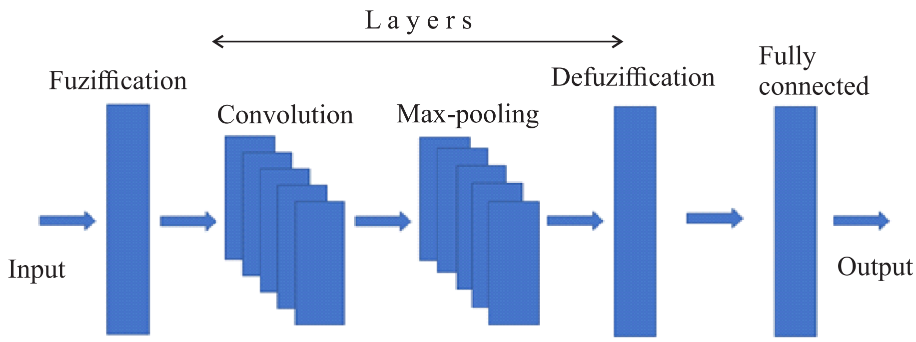

Fig. 1. CFNN structure

channel estimation. A common architecture for a CFNN includes convolutional layers for extracting features from input data and a fully connected layer, which is often identical to that of a standard CNN. The key distinction is the presence of a fuzzification layer that transforms the input data into a fuzzy representation. This allows the network to handle imprecise or uncertain data, and make use of the advantages of fuzzy logic in estimation process. The fuzzification layer can be implemented using various methods such as membership functions, fuzzy sets or fuzzy logic operators. The output of the fuzzification layer is then processed by the convolutional and fully connected layers, to finally make a decision on the output class. In the CFNN, the fuzzification-layer processes the input data to create a fuzzy logic representation [18-19]. The CFNN structure is depicted in Fig. 1.

Fuzzy membership functions are used in fuzzy logic reasoning and decision-making to assign a membership grade, or degree of membership, to each element in a matrix $\boldsymbol{S}$ based on membership functions that map the input data to a value between 0 and 1, with 0 indicating no membership and 1 indicating full membership.

To obtain the fuzzy sets

$$\widetilde{\boldsymbol{S}} = \text{fuzzification}(s_{k,l}|cs_{k,l}), \tag{6}$$

by utilizing the max-product operation

$$\begin{aligned} x_{k,l} &= \text{possibility}(x_{k,l}|\widetilde{GF_{k,l}}) \\ &= \max_{s \in S} \left(\widetilde{GF_{k,l}}\delta(s - s_{k,l})\right) \end{aligned}, \tag{7}$$

to compute the possibilities of the input and output data belonging to fuzzy members $\widetilde{GF_{k,l}}$ in the universe of discourse.

Here the input fuzzy membership function is cs, and the indices of element s in the input matrix $\boldsymbol{S}$ are k and l, and $\delta(s - s_{k,l})$ represents the Kronecker symbol.

The fuzzy convolutional process is composed of three stages: fuzzy convolution, nonlinearity, and pooling, which make up each layer. The fuzzy convolutional process

$$\mathbf{x}_{k,l} = \sum_{a=0}^{m-1} \sum_{b=0}^{m-1} \boldsymbol{W}_{\mu} s_{(k+a)(l+b)}, \tag{8}$$

entails applying fuzzy convolutional filters to 2D inputs. The fuzzy convolutional filters

$$\boldsymbol{W}_{\mu} = \text{fuzzification}\big(\boldsymbol{W}\big), \tag{9}$$

are calculated using (6) with the original convolutional filter, W.

The output achieved from the fuzzy convolution stage is transformed through a non-linear transformation

$$t_{k,l} = \sigma(s_{k,l}), \tag{10}$$

where $\sigma(.)$ represents the activation function of the convolutional layer. Pooling is the final stage, which summarizes the statistics of neighboring outcomes following feature extraction. This step aids in making the representation insensitive to input translation while also potentially reducing the quantity of input to the following fuzzy convolutional layer.

The CFNN's fully connected layer is functioning as a classifier using crisp values from the center of gravity method of defuzzification, represented by

$$z_k = \text{defuzzification}(s_k) = \frac{\sum C_t s_k}{\sum s_k}, \tag{11}$$

where C_t is the center of the defuzzification membership function and

$$\mathcal{C}_k = \text{fullyconnected}(z_k), \tag{12}$$

is the classifier's output, [18-19].

3.1 Training process of CFNN

The output error is assessed using cross entropy as a loss function

$$E = -\frac{1}{N} \sum_{n=1}^{N} \left[t_k \log(\hat{t}_k) + (1 - t_k)log(1 - \hat{t}_k)\right], \tag{13}$$

where $\hat{t}$ denotes the target, t – represents the classifier output, and N is the number of samples [18-19].

The model's parameters are trained with a traditional back-propagation technique and a cross-entropy loss function

$$W_{\mathrm{fc}}(q+1) = W_{\mathrm{fc}}(q) - \alpha_{\mathrm{fc}} \frac{\partial E}{\partial W_{\mathrm{fc}}}, \tag{14}$$

to update the weight.

The update of the defuzzification membership functions

$$c_t(q+1) = c_t(q) + \alpha_{c_t} \nabla_{c_t}, \tag{15}$$

the learning rate of updating the center is represented by $\alpha_{cy})$, t_{q+1} – is the target output, and $\hat{t}_{q+1}$ is the model's actual output.

The centre value C_w and the variance σ of the fuzzification membership function of the convolution layer's weight can be computed with the learning rate α_{c_w}.

4 Simulation results

The performance of the proposed channel estimator has been evaluated by examining the transmission states of the MIMO-NOMA system with various antenna numbers in both Rayleigh and Rician channels. The performance of the proposed CFNN-based symbol detector was evaluated by comparing it with LS-SIC, LMMSE-SIC algorithms, which are classical techniques and CNN-based symbol detector, which is deep learning type. Fig. 2 shows the SNR-BER values of the channel estimators in the MIMO-NOMA system with 2×2 antenna numbers over Rician Fading channel. Although LS-SIC is the most easily applicable symbol detector among the other detector, the LS-SIC has the worst performance. For example, even with LMMSE-SIC, which has the closest performance to LS, there is an SNR difference of 8.5 dB at a BER of 10^{-1}. The proposed CFNN-based detector has the best BER performance value, both at low SNR and high SNR values.

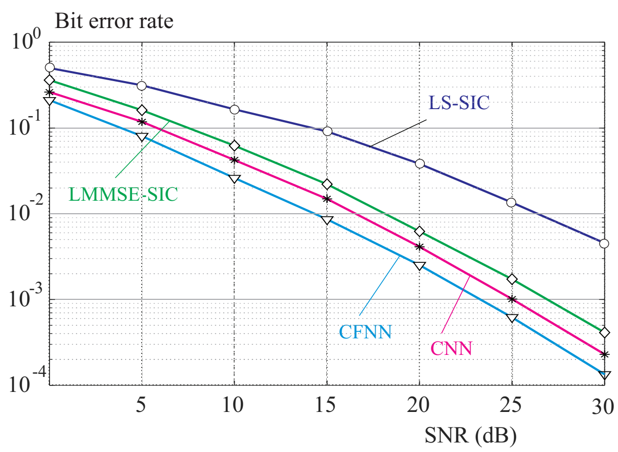

Fig. 2. BER values of 2×2 MIMO-NOMA over Rician fading channel

Transmission in the Rayleigh channel is examined in Fig. 3 to see how the symbol detectors perform in the transmission condition in the channel with high distortion effects. As can be seen from Fig. 3, there is no decrease in the performance of the proposed algorithm even when the channel conditions deteriorate. Moreover, it has a 3 dB SNR gain of 10^{-2} BER from CNN, which has the closest performance value. This gain value is 4 dB according to the LMMSE-SIC, which has the best value among the classical algorithms.

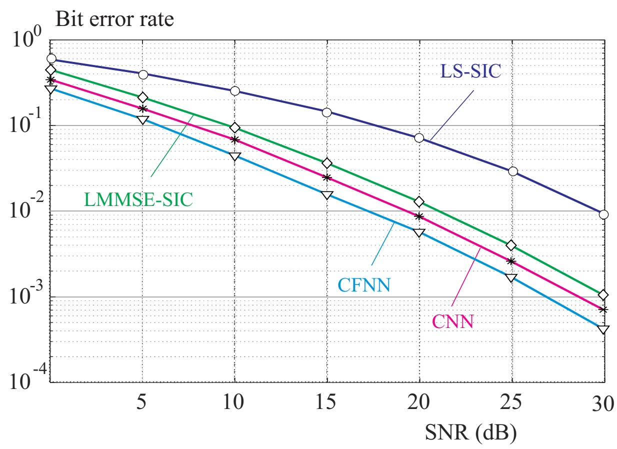

Fig. 3. BER values of 2×2 MIMO-NOMA over Rayleigh fading channel

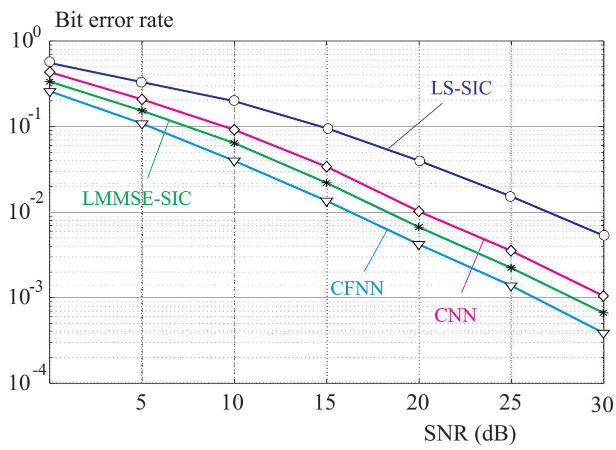

Fig. 4. BER values of 4×4 MIMO-NOMA over Rician fading channel

Figure 4 shows the SNR-BER graph of the transmission state of the NOMA system with a 4x4 antenna structure over the Rician channel. The high number of antennas in communication systems helps to reduce data errors caused by the channel. In this system, where the number of antennas is increased, it is seen that the errors are significantly reduced compared to the 2x2 system. In addition, the performance of the symbol detectors increased with the increase in the number of antennas. As can be seen from the related figure, the CFNN technique has maintained its performance superiority over other methods in systems with 4×4 antenna numbers. On the other hand, it is seen that the proposed method has the best performance in a channel with disturbing channel conditions. For example, considering the values obtained at

10^{-3} BER; in the case of using the CFNN technique for symbol detection, 2-, 4- and 11-dB SNR gains were obtained compared to CNN, LMMSE-SIC and LS-SIC, respectively. In addition, the BER values in Fig. 5 were obtained to observe the performance of the symbol detectors in the Rayleigh fading channel in the 4×4 system. As with the other obtained graphs, the proposed CFNN technique has better BER values than both the classical techniques and the CNN technique.

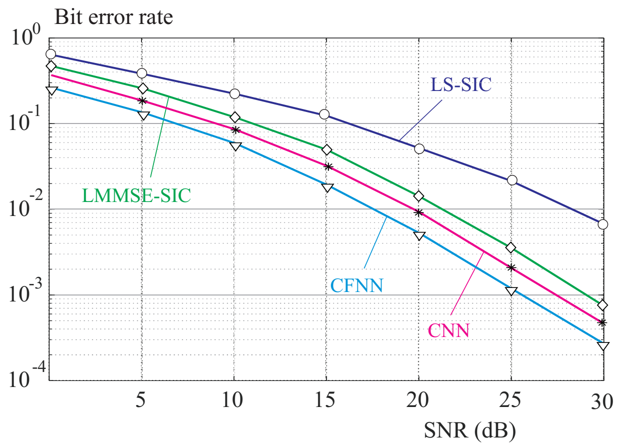

Fig. 5. BER values of 4×4 MIMO-NOMA over Rayleigh fading channel

5 Conclusion

This study proposes the use of the CFNN model, a hybrid deep learning approach that combines the benefits of deep learning and fuzzy logic techniques for symbol detection in MIMO-NOMA systems. Transmission states over Rayleigh and Rician channels are evaluated to assess the efficacy of the proposed approach. With this proposed method, better bit errors rate performance was obtained than the compared CNN, LMMSE-SIC and LS-SIC in the study even when the channel has high distortion. Although the performance of LMMSE-SIC is acceptable for MIMO-NOMA systems, the need for channel statistics information of this algorithm makes it practically unapplicable. From the results obtained, it is clearly presented that the CFNN method has a remarkable performance for symbol detection problem in MIMO-NOMA systems besides it can also be used in different multiplexing methods.

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