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Dynamics Spectrum Sharing Environment Using Deep Learning Techniques

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Abstract:

The recent fast expansion of mobile communication services has resulted in a scarcity of spectrum resources. The challenge of multidimensional resource allocation in cognitive radio systems is addressed in this work. Complicated and dynamic Spectrum Sharing SS systems might be vulnerable to a variety of possible security and privacy vulnerabilities, necessitating protection techniques that are adaptable, dependable, and scalable. Methods based on machine learning (ML) have repeatedly been proposed to overcome these challenges. We present a complete assessment of the current progress of ML-based SS approaches, the most crucial security challenges, and the accompanying protection mechanisms in this paper. We develop cutting-edge methodologies for improving the performance of SS communication systems in a variety of critical areas, such as ML-based cognitive radio networks (CRNs), ML-based database assisted SS networks, ML-based LTE-U networks, ML-based ambient backscatter networks, and other ML-based SS solutions. The results of the simulation trials show that the suggested strategy may successfully boost the user's incentive while reducing collisions. In terms of reward, the suggested strategy beats opportunistic multichannel ALOHA by around 10% and 30%, respectively, for the single SU and multi-SU scenarios.

Keywords: *Spectrum sharing, machine learning, security, CRN, LTE-U, SSDF, PUE, jamming, eavesdropping, and privacy are all things to consider.*

Introduction

Both the cognitive radio (CR) and the multiple access, non-orthogonal (NOMA) scheme have been highlighted as potential alternatives, particularly given the rising demand for efficient satellite resource utilization. Enhancement of spectrum efficiency (Chiti et al., 2005; Kourogiorgas et al., 2017). The SS network can assist alleviate the scarcity of spectrum resources. Unlike typical exclusive spectrum allocations, SS incorporates numerous companies and uses the available spectrum in a shared manner to maximize the efficiency of the limited spectrum resources. According to Kourogiorgas et al. (2017), Guo et al. (2018) and Ruan et al. (2018) there are two types of SS: horizontal sharing and vertical sharing. Lateral sharing implies that all networks and users have equal access to the resources spectrum. Such solutions enable users to coexist harmoniously and effectively. Vertical sharing, on the other hand, permits many types of users to access spectrum assets with varying levels of access. As a result, secondary users (SUs) can use the spectrum without interfering with the performance of the main users (PUs). By allowing SUs to access the spectrum controlled by PUs, the restricted spectrum resource may be used to support additional devices (Ruan et al., 2018; An et al., 2015; Haykin, 2005). A substantial amount of research has been conducted on dynamic spectrum access technology in cognitive radio (CR) systems, with some studies employing game theory to examine spectrum sharing among communication system users Haykin, (2005). The communication system's users are modeled as players, and their access methods are examined. For example, in (Zhou, Zhu, & Ling, 2010), a game-theoretic methodology and utility function for spectrum sharing in CR systems were provided, whereas reference Cai et al. (2016) offered a solution based on game theory and the decision tree. Another study (Ahmad et al., 2014) proposed a pricing mechanism based on the Stackelberg game to enhance spectrum sharing, and researchers created an algorithm to optimize the cost of bandwidth allocation for main users (PU) and secondary users (SU) (Pandit,. & Singh, 2013). Furthermore, the Carnot model was developed.

The goal of this research is to use DRL to address the issue of spectrum sharing and power control in cognitive radio systems. The proposed technique employs Convolution Neural Networks CNN-based training with multiple agents for spectrum access strategy, modeling multiple resource allocation in communication systems as reinforcement learning, and constructing a reward function for users as shown in figure (1).

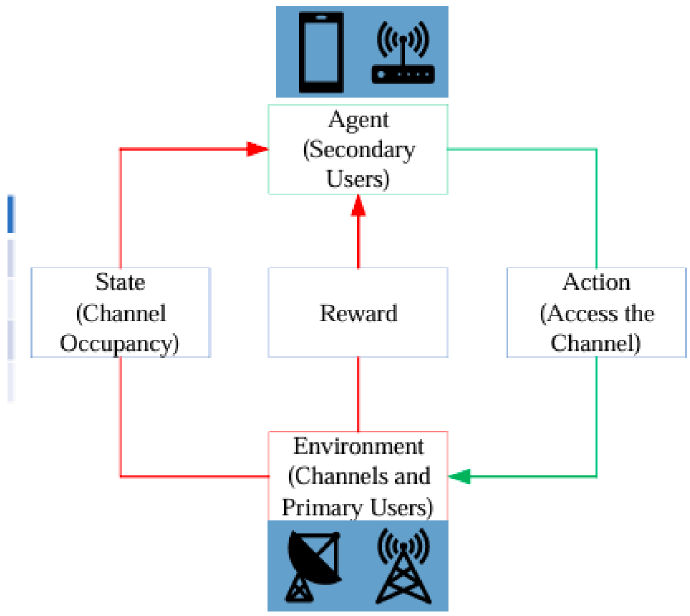

Figure 1. Principle of CNN Spectrum Sharing Techniques

The training also includes freezing target networks and experience replay, and the algorithm's complexity is assessed. The simulation findings show that secondary users (SU) may learn how to access the spectrum successfully through training using the proposed technique in both single SU and many SU scenarios.

The following is the paper's structure. Section 2 discusses the system model, Section 3 outlines the suggested CNN-based spectrum sharing approach and training algorithm, Section 4 displays the simulation results, and Section 5 summarizes our findings results.

Problems Formulation (System Modelling)

This model takes into account an SS. The system is made up of M primary users who belong to a certain cluster, S secondary satellites that provide information, R secondary terrestrial relays, and SU1 and SU2 secondary terrestrial users. There is only one antenna on each node.1 We predict that S is unable to transfer messages directly to SUi (i =1,2) due to excessive shadow fading. R helps S communicate with SUi.

In addition, the decode-and-forward (DF) protocol is used on R, which operates in half-duplex mode. Because of the large distance between the PT and R or SUi, the primary transmitter (PT) is not expected to interact with them. In the recommended model, two time slots are required to complete the transmission (Zhang et al., 2020; Han, Zhu, & Lin, 2021). In the first time slot, S sends messages to R utilizing the superposition coding method (SCT) of the NOMA scheme, which can integrate two signals. The signal to R (Zhai, & Du, 2017) is supplied by:

$$\boldsymbol{s}=\left(\sqrt{\boldsymbol{\beta_1 P_S s_1}}+\sqrt{\boldsymbol{\beta_2 P_S s_2}}\right) \qquad (1)$$

PS denotes S's transmission power, si (i = 1, 2) denotes the message to SUi, and i denotes the power allocation factor (1+2=1)." Without sacrificing generality, we suppose that R to SU1 has a poorer channel condition than R to SU2, thus 1 > 2. As a result, the signal received at R may be represented as (Yan et al., 2018; Zhang et al., 2020):

$$y_R = h_{SR}\left(\sqrt{\boldsymbol{\beta_1 P_S s_1}}+\sqrt{\boldsymbol{\beta_2 P_R s_2}}\right)+n_R \qquad (2)$$

where h_{SR} is the channel coefficient between S and R, nR is the additive white Gaussian noise (AWGN) at R: with n_RCN (0,2_R). The DF protocol and SCT are used at R in the second time slot to send the received signal to SUi. Then

$$y_i = h_{SU_i}\left(\sqrt{\boldsymbol{\beta_1 P_R s_1}}+\sqrt{\boldsymbol{\beta_2 P_R s_2}}\right)+n_i \qquad (3)$$

where P_R represents R's transmission power and h_(SU_i) represents the Rayleigh fading-affected channel coefficient. We can compute the signal to interference plus noise ratio (SINR) of s_i at R using (1):

$$\gamma_{s1} = \frac{I_{\gamma SR}\beta_1}{I_{\gamma SR}\,\beta_2+\gamma SP\sigma^2{}_R} \qquad (4)$$

$$\gamma_{s2} = \frac{I_{\gamma SR}\beta_2}{\gamma SP\sigma^2{}_R} \qquad (5)$$

Results and Discussion

A-Simulation Setup

The (CNN) is one of the most widely used approaches to optimization in recent years. CNN may have included several unrealistic alternatives in an effort to address a different problem, which has a detrimental impact on how the computation is portrayed. Figure (2) depicts the schematic diagram for the problem statement.

During CNN flowchart is shown in figure (3) training, rather than scrambling the order, the sequential information is kept when updating the neural network weights. For computation, the neural network processes continuous sequences of input. When updating parameters, it is difficult to execute gradient descent on data from a single time slot due to RNN features. Instead, the gradient of each network weight must be calculated using the backpropagation over time approach.

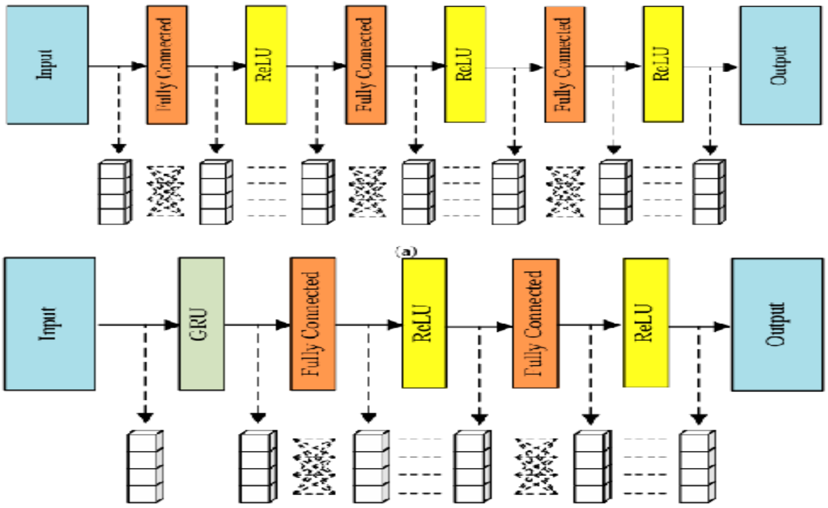

Figure 2. General CNN Structure

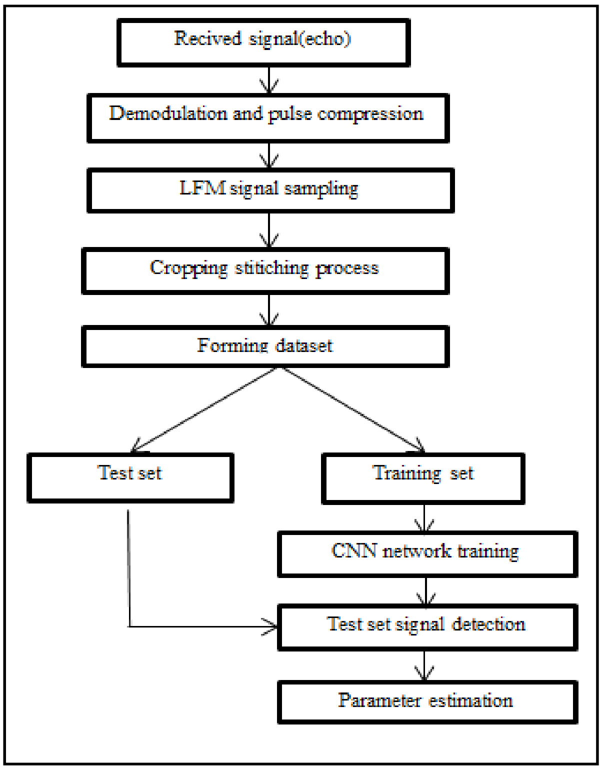

Figure 4. CNN Flowchart

B-Simulation Results

This section evaluates the performance of the NOMA uplink scenario using the suggested power-control technology and evolutionary algorithm. The suggested solution's result is determined using the MATLAB tool during the simulation stage, which is also used to examine the proposed scheme's SE-EE tradeoff. The simulation parameters were provided in Table 1.

Table 1. Simulation Setup Parameters

No.	Description	Value
1	Distances of users from base station (BS)	d1=1000m,d2=500m
2	Path loss exponent	$\alpha=4$
3	Number of PU	15
4	Power allocation factor	$0<\beta<1$
5	Number of SU	1
6	Active Rate	1
7	Selectable Transmission Power	20 mW
8	Learning Rate	0.02

Create a semantic segmentation neural network using the deeplabv3plusLayers (Computer Vision Toolbox) function to implement transfer learning. Select the input picture size (the number of pixels used to depict the time and frequency axis) and the number of classes. Resnet50 should be chosen as the basis network (by specifying the value of base Network). The function offers a link to the necessary support package in the Add-On Explorer if the Deep Learning Toolbox TM Model for ResNet-50 Network support package is not installed. Click the link, then select Install to start the support package installation. Enter resnet50 at the command line to verify that the installation was successful. The function returns a DAG Network object in the event that the necessary support package is installed.

Plotting the pixel counts by class label using the count EachLabel (Computer Vision Toolbox) function will show you the distribution of class labels in the training dataset.

Ideally, there should be an equal amount of observations in each class. However, it is typical for the training set's courses to be unbalanced when using wireless signals. 5G NR transmissions are noisy in the background and may have a wider bandwidth than LTE signals. An imbalance in the number of observations per class might be harmful to the learning process since the learning is skewed in favor of the dominating classes. Class weighting is employed in the section Balance Classes Using Class Weighting to reduce bias resulting from an imbalance in the number of observations per class.

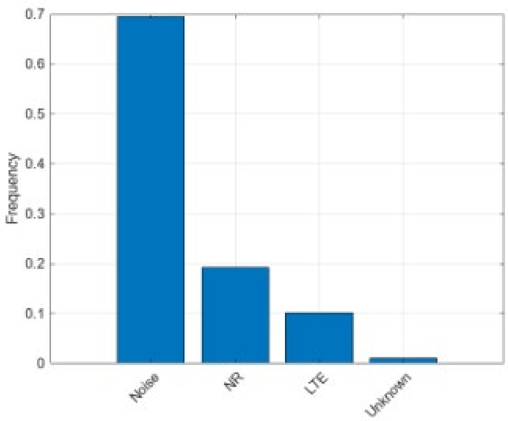

Figure 5. Histogram of Spectrum Sharing

Ideally, there should be an equal amount of observations in each class. However, it is typical for the training set's courses to be unbalanced when using wireless signals. 5G NR transmissions are noisy in the background and may have a wider bandwidth than LTE signals. An imbalance in the number of observations per class might be harmful to the learning process since the learning is skewed in favor of the dominating classes. Class weighting is employed in the section Balance Classes Using Class Weighting to reduce bias resulting from an imbalance in the number of observations per class.

Create a basic network for semantic segmentation. You may skip this step and go directly to apply a Pretrained Network for Transfer Learning if you would want to apply transfer learning on a pretrained network instead. Down sampling an image between convolutional and ReLU layers, followed by upsampling the output to match the input size, is a typical trend in semantic segmentation networks. Non-linear filters that are tailored for the particular classes you need to segment are used by a network to carry out the activities throughout this procedure. The simulation results for separation unknown signal shown in figure (6).

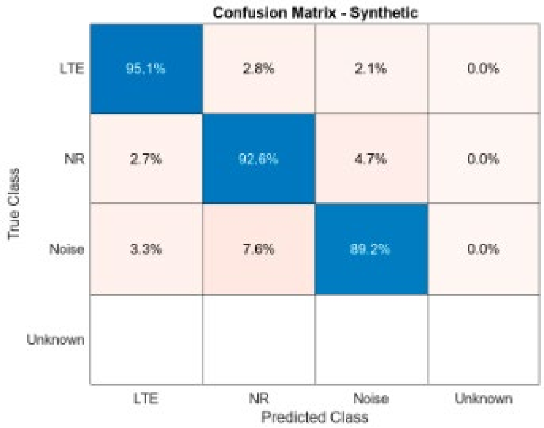

Figure 6. Confusion Matrix for Simulation Results

Where when we considered the unknown signals as part of classification process the results is shown in figure (7).

The network mixes NR signals with noise or unknown signals, as the confusion matrix demonstrates. Upon closer inspection, it can be seen that the signals with the noise have extremely low signal-to-noise ratio (SNR) and are difficult for the network to appropriately detect.

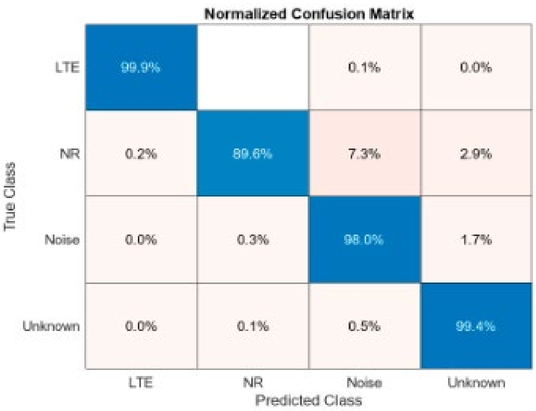

Figure 7. Confusion Matrix

Conclusion

In this work, we investigated the efficacy of a spectrum sharing based CNN with different PUs. Specifically, closed-form formulas for the OP and EC were generated for the proposed arrangement. At high SNRs, asymptotic OP expression might potentially be produced. It is clear that when PUs were decreased, system performance rose. Furthermore, power distribution factors and rate thresholds had a big influence on the system's performance. Furthermore, we found that for low SNRs, EC decreased as β1 increased and that, depending on the system characteristics, there were numerous optimum values for β1 to reduce OP. Furthermore, when rate thresholds climbed, OP would grow.

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