Optimization and Transmit Power Control Based on Deep Learning with Inaccurate Channel Information in Underlay Cognitive Radio Network

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Abstract. In cognitive radio network (CRN), power control often faces the complicated iterations and large calculations, resulting in poor real time performance of the system. In this paper, a deep learning-based power control is proposed for CRNs, where the secondary users (SUs) can share the same channel of primary users (PUs) without causing excessive interference to the communication of PU. In the novel scheme, the DNN model is used to treat the input and output of the power control algorithm as unknown non-linear mappings and fit them, which determines the proportion of transmit power allocated to each SU, considering the interference caused to the PU. With this scheme, the maximization of the SUs sum-rate can be achieved. Furthermore, due to some errors in the practical samples of channel information, an auto-encoder is used to compress the channel coefficient through an encoder and reconstruct them through a decoder before DNN training. The simulations results show that the power control method using a combination of auto-encoding and DNN can improve the real-time performance of the system. And the sum-rate of SU is improved while the interference caused to the PU can be regulated even with the inaccurate channel information.

Keywords: Cognitive radio network; Power control; Auto-encoder; Deep neural network.

1. Introduction

In recent years, with the explosive growth of mobile devices and the advent of the 5G, people have increasing demands for radio equipment and applications increasing demands for spectrum resource [1]. How to allocate spectrum resources has become an important issue. Cognitive radio uses spectrum sensing technology to sense surrounding environment and find available spectrum, through opportunistic spectrum access or overlapping spectrum access, allows PUs and SUs to share spectrums[2]. The opportunistic spectrum access method allows SUs to use spectrum when the PUs are not using. In particular, if the interference caused by SUs to PUs is less than PU interference threshold, the underlay spectrum access method allows the PUs and the SUs to transmit data on the spectrum of a Pu. Resource allocation is one of the key technologies in the underlay CRN which improve the overall system performance of the CRN by allocating parameters such as best channel and optimizing power for the SUs without interrupting the PUs[3]. Accordingly, in order to ensure communication of the PUs and SUs, transmit power of SUs must be strictly controlled in the underlay CRN.

The current research on power control of CRN includes power control based on game theory and optimization theory. [4] uses the auction mechanism to allocate transmit power to SUs. The basic idea is that each SU submits a quote according to his own communication needs and decision maker is
based on the quote submitted by each SU. Theoretical analysis proves that the algorithm can obtain the only optimal power allocation result and can obtain the efficiency close to Pareto's optimal and a certain user fairness. [5] modeled the cognitive radio network based on overlay spectrum sharing as a joint formation game, and then designed a power allocation algorithm. [6] used optimization theory to study the resource allocation strategy to maximize the total capacity of cognitive radio network systems. In most previous works on power control, optimization problems are complicated and require large computational overhead, hindering real-time operation.

Deep learning has become more important in the application of wireless communication resource allocation. In advantage of character representation of deep learning, which can reduce the computational complexity and power allocation can actually be regarded as a nonlinear mapping between input and the final allocation result [7]. [8] proposes a scheme based on convolutional neural network which introduces the rate sum into the loss function. Compared with the traditional power allocation scheme, it reduces the time without affecting the rate of users. [9] takes into account the spectral efficiency in the DNN-based power allocation process and improves the signal-to-noise ratio. [10] uses Weighted minimum mean square error (WMMSE) to get the power allocation of users in wireless communication as the output of neural network, combines the channel coefficient as the input of neural network and allocates the power to users based on DNN method which greatly improves the real-time performance of the system. [11] bases on the deep reinforcement learning and WMMSE algorithm considering spectrum access and power control and choosing the strategy according to the feedback of actions which can get the joint control method. WMMSE algorithm is used in general wireless communication networks for resource allocation to maximize the system rate sum. However, it is necessary to consider the interference between SUs and PU and the interference between SUs and the traditional WMMSE algorithm is not applicable. In addition, the damaged channel information is corrected by denoising autoencoder (DAE) before using DNN-based power control scheme to which improve the accuracy of the scheme considering of the negative impact of the inaccuracy channel coefficient [12].

This paper proposes a method based on DNN and DAE for CRN. The idea is to treat a given power control optimization algorithm in CRN and learn input/output by using DNN with inaccuracy channel coefficient. The contributions as follows:

1) Considering the inaccuracy channel information of actual conditions, an auto-encoder is used to reduce noise, then DNN is used to maximize sum-rate of SUs. Meanwhile, communication quality of the PU and SUs also can be considered.

2) Different from normal wireless communication system, the paper considers the interference caused to the PU by the SUs in the power control scheme.

3) The scheme is certified by simulations. Results shows that can improve the real-time of system and achieve high sum-rate with limited PU interference caused by SUs even the channel gain with error information.
2. System Model

Figure 1. The system model of the underlay CRN.

In cognitive radio network model, this paper assumes that there exists a PU transceiver pair and $K$ SU transceiver pairs (TPs). However, the $K$ single-antenna SU TPs who do not own the wireless channel and want to use the same spectrum resources of the PU opportunistically, and the set of SU TPs is denoted by $K$, as shown in Figure 1. The transmit of power of $SU_k$ TP allocated to the PU channel is denoted as $p_k$, where $0 \leq p_k \leq P_M$, $P_M$ is the maximum transmit power. Let $h_{ij} \in \mathbb{C}$ denotes interference channel gain from the SU transmitter $j$ to the SU receiver $i$ in PU channel. Furthermore, the paper assumes that the channel gain $h_{ij} \in \mathbb{C}$ are circularly symmetric complex Gaussian distributed (CSCG), i.e. $h_{ij} \sim N(0,1)$. Assume that the channel gain from different transmitters are independent. In transmission process, SUs need to be allowed to occupy the spectrum of PU and select power to transmit symbol. The signal-to-interference-plus-noise ratio (SINR) of $SU_k$ can be formulated as

$$\text{SINR}_k = \frac{p_k |h_{k,k}|^2}{\sum_{j\neq k} p_j |h_{k,j}|^2 + \sigma_i^2 + p_0 |h_{0,0}|^2}$$

(1)

The SINR of PU can be formulated as

$$\text{SINR}_{PU} = \frac{P_0 |h_{0,0}|^2}{\sum p_j |h_{0,j}|^2 + \sigma_0^2}$$

(2)

Where $\sigma_i^2$ and $\sigma_0^2$ is variance of the Gaussian noise at receiver $k$ and receiver PU.

3. Improved WMMSE Algorithm for CR

WMMSE is used to maximize sum-rate in the ordinary wireless network [11]. In the paper, it is modified to fit the cognitive radio communication. To maximize sum-rate of the SUs, formulation can be wrote as

$$\max \sum_{i=1}^{K} \log(1+\text{SINR}_i)$$

s.t. $0 \leq p_k \leq P_m, k = 1, 2, 3, ..., K$

$$\text{SINR}_{PU} \geq \gamma_{PU}, \text{SINR}_{SU} \geq \gamma_{SU}, k = 1, 2, 3, ..., K$$
Where $\gamma_{PU}$ and $\gamma_{SU}$ denote the minimum SINR acceptable to primary users and cognitive users. In [10, 11], P1 is known to be NP-hard problem that solve problem by introducing a new variable $mmse_k = 1/(1 + SINR_k)$. On the other hand, considering the inaccuracy channel state information [12], denoising autoencoder is used to corrected the corrupted channel coefficient. P1 of maximizing rate sum is equivalent to P2 of minimizing mean square error [10], and details are in Algorithm 1:

$$\min \sum_{k=1}^{K} (w_k e_k - \log(w_k))$$

s.t. $0 \leq v_k \leq \sqrt{P_u}, k = 1, 2, 3, ..., K$

$SINR_{PU} \geq \gamma_{PU}, SINR_k \geq \gamma_{SU}, k = 1, 2, 3, ..., K$

Algorithm 1: WMMSE for power control in CRN

Input: $h_{k,j}$

for each scheme of power control do

Initialize: $0 \leq v_k^0 \leq \sqrt{P_u}, \forall k$;

Compute:

$\nu_k^0 = \frac{1}{\sum_{j=1}^{K} |h_{k,j}|^2 + |v_k^0|^2}, \forall k$;

Compute $\omega_k^0 = \frac{1}{1 - |v_k^0|^2}, \forall k$;

for iteration $t=1, 2, 3, ..., T$ do

Update $\nu_k^t$: $\nu_k^t = \frac{\nu_k^{t-1} - \nu_k^0 |h_{k,j}|^2}{\sum_{j=1}^{K} \nu_k^{t-1} |h_{k,j}|^2}, \forall k$;

Update $\nu_k^t$: $\nu_k^t = \frac{\nu_k^{t-1} |h_{k,j}|^2}{\sum_{j=1}^{K} |h_{k,j}|^2 |\nu_k^{t-1}|^2 + \sigma_k}, \forall k$;

Update $\omega_k^t$: $\omega_k^t = \frac{1 - |v_k^{t-1}|^2 |\nu_k^{t-1}|^2}{1 - |v_k^{t-1}|^2 |\nu_k^{t-1}|^2 + \sigma_k}, \forall k$;

if satisfy the following conditions:

(1) $\sum_{j=1}^{K} \log_2(\omega_j^t) - \sum_{j=1}^{K} \log_2(\omega_j^{t-1}) \leq \varepsilon$

(2) $\sum_{j=1}^{K} \frac{P_i |h_{k,j}|^2}{\nu_k^t |h_{k,j}|^2 + \sigma_k} \geq \gamma_{PU}$

(3) $\sum_{j=1}^{K} \frac{P_i |h_{k,j}|^2}{\nu_k^t |h_{k,j}|^2 + \sigma_k} \geq \gamma_{SU}$

then

break;

end

end

Output: $p_k = \{\nu_k\}^2, \forall k$;

4. Proposed Transmit Power Control Scheme

In proposed scheme, data preprocessing is composed of two parts: autoencoder for samples and a DNN-based power control that maximizes the sum-rate while ensuring the communication quality of SUs. The main theory of denoising autoencoder is: introduce interference into the input before encode and decode input which after decoding remains the same as the original input. If the input can be reconstructed to the input with interference, then the network is robust to the input. The data reconstructed by denoising autoencoder is used as the input of the DNN which can reduce the error information of channel characteristics and improve the accuracy and robustness of the DNN-based power control scheme. 4.1. The Theoretical Knowledge of Denoising Autoencoder and DNN
4.1.1. Denoising autoencoder.

A denoising autoencoder is aimed to reconstruct input. During reconstruction process, noise contained in the original data will be removed (or the erroneous data will be corrected). The structure of the denoising autoencoder is shown in Figure 2. Randomly add noise to the original input data $x$ to get the corrupted data $\hat{x}$, then the encoder maps the corrupted data $\hat{x}$ to the hidden layer through the encoding function $f$ to get the compressed feature $h$, uses the decoding function $g$ to map the feature $h$ of the hidden layer to the output layer to get the reconstruction of the corrupted data, the output vector $y$. The processing of encoding is:

$$h = f(\hat{x}) = \alpha_1 (w_1 \hat{x} + b_1)$$  \hspace{1cm} (5)

The processing of decoding is:

$$y = g(h) = \alpha_2 (w_2 h + b_2)$$  \hspace{1cm} (6)

The loss function of the denoising autoencoder is:

$$J = \sum L(x, g(f(\hat{x})))$$  \hspace{1cm} (7)

The difference between denoising autoencoder and traditional autoencoder is that part of the input of denoising autoencoder is damaged during the training process. It encodes and decodes the corrupted original data to restore the original data. As shown in Figure 3, $x$ is randomly destroyed to $\hat{x}$ and autoencoder maps it to $h$ and reconstruct $x$ via decoder $g$, producing reconstruction $y$.

![Figure 2](image.png) **Figure 2.** The model of power control based on AE and DNN.

![Figure 3](image.png) **Figure 3.** The denoising autoencoder architecture.

4.1.2. Deep neural network. DNN is neural network with hidden layers: input layer, hidden layers and output layer. Hidden layers are composed of a linear relationship function and an activation function, and operation called dropout is added after each hidden layer. Because of the simple structure and limited complexity of liner function, its representation ability is not strong. Without the activation function, the neural network which only a liner function cannot learn and represent complex feature. The activation function provides the neural network with a nonlinear modeling ability that the neural
network has the learning ability of layered nonlinear mapping. The Dropout operation randomly reduces the weight or output of the hidden layer to zero to reduce the association between nodes and prevent the network from over-fitting or gradient disappearing due to excessive parameters. In addition, nonlinear activation function is a significant module in neural networks. The common activation functions have rectified linear unit, hyperbolic tangent function \( \tanh \) and sigmoid function. Since the activation function is nonlinear function, taking the output of the previous layers as the input of the activation function, non-linear features can be introduced into the neural network, so that the neural network can fit more functions and handle more complex problems. Activation functions are:

\[
f_{\text{Relu}}(x) = \max(x, 0) \tag{8}
\]

\[
f_{\tanh}(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \tag{9}
\]

\[
f_{\text{Sigmoid}}(x) = \frac{1}{1 + e^{-x}} \tag{10}
\]

Assuming it has \( m \) neurons in hidden layer \( n \) and the output vector is \( \{a_1^n, a_2^n, a_3^n, ..., a_m^n\} \), then output of neuron \( j \) in layer \( n+1 \) is

\[
a_j^{n+1} = \sigma \left( \sum_{i=1}^{m} a_i^n + b_j^{n+1} \right) \tag{11}
\]

where \( \sigma(\cdot) \) denotes activation function, \( b_j^{n+1} \) denotes the biases in the hidden layer \( m+1 \). Hidden layer calculates the data and outputs the data to the next layer, repeat the steps can get the output of the entire neural network. Profit the efficient learning ability of DNN to learn the non-linear mapping relationship between the channel status information of primary users and cognitive users and the allocated power of cognitive users, adjust the parameters of DNN then adaptively generate the optimal power that satisfies PI requirements.

4.2. Structure of Denoising Autoencoder and DNN for Power Control

The paper proposed model is composed of a autoencoder net and a DNN. The input of the model is the channel gain that is denote as \( h_{ij} \) and the output denote as \( p_i \in \{p_1, p_2, p_3, ..., p_K\} \) is the transmit power which is allocated to SUs. This paper uses a denoising autoencoder to compress sample data with erroneous channel coefficient and train a DNN to compress sample data with erroneous information, then use the decoder to restore the data. The weights of the encoder and decoder are initialized, then to minimize the error between the original training data and the reconstructed and restored data, the denoising autoencoder is trained. The denoising autoencoder is consisted by the encoder and the decoder, and the detail of the process in formula (5) and formula (6). The number of nodes in AE is as follows: three hidden layers, an input layer and an output layer. The first and third hidden layer contains 128 neurons, the second hidden layer contains 64 neurons. The input and output are compressed by the encoder.

In the DNN part, the input is the autoencoder’s output and the output is the transmit power we calculate. Each hidden layer is composed of fully convolutional networks (FCN) and activation function. The parameters of DNN are as follows: three hidden layers, an input layer and output layer. The input of DNN is a set of channel coefficients and its size depends on the channel model and the output is the obtained power distribution matrix.

4.3. Training Processing

In the proposed scheme of the power control, before using a neural network for fitting, the first step is to prepare the input data. A random number obeying the standard Gaussian distribution is used as the channel coefficient \( h_{ij} \) and the imperfect channel coefficient \( \tilde{h}_{ij} = h_{ij} + \delta, \delta \sim N(0, \sigma^2) \) is used to
add noise to the original data. In denoising autoencoder, the \( \{ h_{ij} \} \) as the input and output to adjust and optimize the parameters in neural network. The loss function of the denoising autoencoder is the mean square error. The optimization algorithm is Adam. After initializing the weights, the denoising autoencoder is training. After training, the inaccurate channel gain can be sent to the trained denoising autoencoder model for processing, and the corrected channel gain obtained after processing is used as the input of the trained DNN model. The structure and train of the DNN model is same as the denoising autoencoder.

5. Performance Evaluation

5.1. Simulation Setup

In simulation, the network composes of input layer, output layer and hidden layers. The number of neurons in three hidden layers is 120, 80, 64. The learning rate is assumed to 0.001 and the optimizer is Adma. According to the result of the Table 1, ReLu is used to be the activation function that can fit more functions and handle more complex problems.

|           | ReLu | Tanh | Sigmoid |
|-----------|------|------|---------|
| DAE       | 95.8%| 93.7%| 93.3%   |
| DNN       | 94.9%| 93.4%| 94.1%   |

The inputs of system depend on the channel coefficients according to CSCG. This article also assumes that the cognitive radio network consists of 10 SUs and a PU, the power limit is 1W, their noise is the 1W, and the SINR threshold of the primary user is -9.03dB. In addition, all the simulations were ran on the Python 3.6 with Tensorflow 1.4.0 and the CPU is AMD Ryzen 5 2600X 3.6GHz with 6 cores.

5.2. Performance Results

![Figure 4](image)

Figure 4. The SINR of PU and SUs in different methods.

The sum-rate performance with the DNN based the WMMSE in CRN that can be evaluate by the 4 schemes:(1) the WMMSE in CRN; (2) the random power control method (rd); (3) every SU selects the maximum power (mp);(4) DNN-based scheme [10]. Figure 4(a) plots the SINR of PU in different methods which can show the SINR of primary user is satisfied and cognitive users can communicate normally. Figure 4(b) illustrates that SINR of cognitive users under DNN-based power control scheme is obviously better than the scheme of allocating maximum power or random allocation for each cognitive user.
Figure 5 describes the sum-rate of CDF under different schemes in the cognitive radio network. "WMMSE" indicates the system transmission rate of the cognitive users obtained using the WMMSE algorithm; "DNN" indicates the system transmission rate obtained using the data without noise as the input to the DNN; "HDWN" indicates the channel gain using the white Gaussian noise. The system transmission rate obtained by fitting as DNN input; "AE-DNN" is the system transmission rate obtained by using the AE network for data containing incorrect channel information and using the corrected data as input to the DNN model. The DNN-based power control schemes compared to the WMMSE algorithm in CRN, the former is 5% less than the latter. And the result of denoising scheme is better than that have imperfect channel coefficients.

6. Conclusion

The paper mainly studies the power allocation of cognitive users in cognitive radio networks, and proposes a method for pre-processing channel characteristics before training. By pre-processing the original data and reconstructing the input, when the relevant data of the channel characteristics are in error, the fault tolerance rate can be improved, then neural network is used to fit the channel characteristics and the power to be allocated to maximize the sum-rate. The experimental results show that after processing the input with the wrong channel gain by the autoencoder and fitting it with the DNN network, the transmission rate is significantly improved, and the time required for calculation is greatly reduced.

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References

[1] Ahmad W S H M W , Radzi N A M , Samidi F S , et al. 5G technology: towards dynamic spectrum sharing using cognitive radio networks[J]. IEEE Access, 2020, PP(99):1-1.
[2] Wotaif A H , Hamza B J , Saad W K . Spectrum Sensing Detection for Non-Stationary Primary User Signals Over Dynamic Threshold Energy Detection in Cognitive Radio System[J]. Al-Furat Journal of Innovations in Electronics and Computer Engineering, 2020, 1(2):26.
[3] Lin Xu , Zhijin Zhao. Channel and Power Allocation Algorithm Based on Distributed Cooperative Q Learning[J]. Computer Engineering, 2019.
[4] Huang J, Berry R A, Honig M L. Auction-based spectrum sharing [J]. Mobile Networks and Applications, 2006, 11(3): 405-18.
[5] Saad W, Han Z, Debbah M, et al. Coalitional Games for Distributed Collaborative Spectrum Sensing in Cognitive Radio Networks [J]. IEEE Infocom 2009 - IEEE Conference on Computer Communications, Vols 1-5, 2009, 2114-22.
[6] Dashti M, Azmi P, Navaie K. Radio resource allocation for orthogonal frequency division multiple access-based underlay cognitive radio networks utilising weighted ergodic rates [J]. Iet Communications, 2012, 6(16): 2543-52.

[7] B. Ozbek, M. Pischella and D. Le Ruyet. Energy Efficient Resource Allocation for Underlaying Multi-D2D Enabled Multiple-Antennas Communications[J]. IEEE Transactions on Vehicular Technology, 2020, 69(6): 6189-6199.

[8] Dai M, Huang Q, Lu Z, et al. Power Allocation for Multiple Transmitter-Receiver Pairs under Frequency-Selective Fading Based on Convolutional Neural Network[J]. IEEE Access, 2020, PP(99):1-1.

[9] Woongsup L. Resource Allocation For Multi-Channel Underlay Cognitive Radio Network based on Deep Neural Network[J]. IEEE Communications Letters, 2018:1-1.

[10] Sun H, Chen X, Shi Q, et al. Learning to optimize: Training deep neural networks for wireless resource management[C]/ 2017 IEEE 18th International Workshop on Signal Processing Advances in Wireless Communications (SPAWC). IEEE, 2017.

[11] Lu Z, Gursoy M C. Dynamic Channel Access and Power Control via Deep Reinforcement Learning[C]/ 2019 IEEE 90th Vehicular Technology Conference (VTC2019-Fall). IEEE, 2019.

[12] Kim M, Kim N I, Lee W, et al. Deep Learning-Aided SCMA[J]. IEEE Communications Letters, 2018, 22(4):720-723.