Machine Learning Based 5G RAN Slicing for Channel Evaluation in Mobile State

Fangpei Zhang[1], Xiaojun Jing[2], Junsheng Mu[2](✉), Jia Zhu[2], and Bohan Li[3]

[1] Information Science Academy of China Electronic Technology Group Corporation, Beijing 100086, China

[2] School of Information and Communication Engineering, Beijing University of Post and Telecommunications, Beijing 100876, China

mujs@bupt.edu.cn

[3] University of Southampton, Southampton, UK

Abstract. The number of mobile broadcast users has increased significantly because of evolved multi-media broadcast multicast services (eMBMS). According to the above reasons, machine learning technology is introduced into 5G RAN slices to forecast the state of communication channel in a mobile scene. We propose a new architecture not only including convolutional neural network (CNN), but also fusing long short-term memory network (LSTM) to implement channel estimation, simultaneously demonstrate the performance of our proposed scheme with simulation results.

Keywords: Machine learning · 5G RAN slicing · Channel estimation

1 Introduction

Under the background of the increasing demand for mobile communication, how to communicate reliably, quickly, and with a low delay has become an urgent problem to be solved. Because of the flexibility of its function, network slicing is adopted by 5G operators to better adapt to the various needs of mobile networks.

We consider two types of segments in 5G RAN, not only including ultra-Reliable low-latency Communications (uRLLC), but also including enhanced Mobile Broadband (eMBB). Based on the obtained channel states, various types of resources can be reasonably allocated to the base station. First, to build a two-dimensional mobile user data set, we should collect multiple signals. Then, CNN-LSTM networks are constructed by combining sequence information and spatial information, on the basis of information, the channel dynamics can be estimated and predicted. Finally, based on the channel information, by using DQN the radio resource allocation can be optimized and the best energy can be obtained. The validity of the proposed scheme is verified through simulation calculation.

S. Sun et al. (Eds.): ICSINC 2021, LNEE 895, pp. 103–107, 2022.
https://doi.org/10.1007/978-981-19-4775-9_12

The key contributions of the paper are summarized below.

(1) We studied 5G RAN network slices for broadcast services. Accordingly, there is currently no solution addressing the physical layer for broadcast applications, which is used to sustain network slicing.
(2) A new architecture is proposed, not only including CNN, but also fusing LSTM, and the channel state of mobile users can be estimated. We use the CNN module to extract spatial features in the channels and the LSTM module to extract time series.
(3) We develop RRM based on DQN for 5G RAN network slice to employed broadcast service performance in mobile computing environment. In particular, energy efficiency is expressed mathematically under certain data rate and delay constraints.

The rest of the paper is arranged as follows. Section 2 presents related work of other researchers and highlights the uniqueness of our contribution to review related work. Section 3 presents the overall of the proposed system model and completes the target problem by mathematical derivation. Section 4 demonstrates the performance of our designed system through simulation studies. Finally, we conclude the paper in Sect. 5.

2 Related Work

Based on virtualization technology, network slicing enables multiple logical network projects to share the physical network infrastructure. Network slicing (NS) maintains the independence of each logical network while allowing for network features such as bandwidth, latency and capacity. Network Function Virtualization (NFV) migrates network function from dedicated hardware to virtual machines on general equipment by using virtualization technology. In addition, these independent network functions can be customized to the user's needs, including network resources, compute resources and storage resources. Network slicing is a key technology for 5G, it can not only be combined with 5G, but also applied to traditional networks.

With the advancement of computing ability and NFV technologies, network slicing technology attracts more and more attention. NS can meet the service requirements of different types applications. In [1], the authors introduce NS from the perspective of the development of NS. In [2], the authors propose a new generic framework that NS can adopt diffusely.

3 System Model

The main of our work is devoted to the downlink of a 5G broadcasting network in which a number of N base stations and user equipment (UE) are randomly put up. To represent the placement of BSs, A Homogeneous Poisson Point Process (HPPP) Φ with an arrival rate of λ_b is implemented. In addition, an HPPP Φ_u with a density of λ_u represents UEs deployment, and it is independent of the process Φ_b. B represents the system bandwidth, and P_b represents each BS power. [t, t + 1) defines the time slots where the period of τ for each slot is t. It connects each BS that owns data queue buffer.

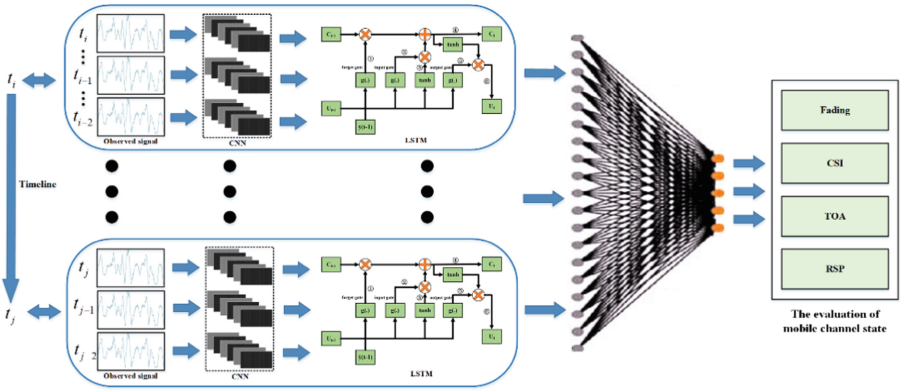

Fig. 1. A framework that combines CNN and LSTM.

The network resources will be partitioned accordingly to the demand of each user. We assume that there are two types of slices, respectively named uRLLC and eMBB. uRLLC and eMBB are the different slices in the network, respectively. The bandwidth coefficient assigned to Slice s (s = 1, 2) is represented as $p_s(t)$, and the power coefficient assigned to Slice s (s = 1, 2) is represented as $b_s(t)$, where $0 < p_s(t) < 1$, $0 < b_s(t) < 1$.

Suppose the sensed signal $y(n)$ at the base station of user consists original signal $s(n)$ and additive white Gaussian noise (AWGN) $x(n)$ then.

$$y(n) = h(n)s(n) + x(n), \tag{1}$$

where $h(n)$ indicates channel gain and $|h(n)|$ is *Nakagami* distribution. $s(n)$ and $x(n)$ are independent identically distribution, and their mean zero and variance are σ_{s-i}^2, σ_{x-i}^2 respectively (iid).

For the process of the proposed method, the signal enters the channel and undergoes a series of processes to obtain the corresponding channel characteristics [3]. First, the input two-dimensional signal data is derived from the received time domain one-dimensional signal by frequency transformation. Then, the convolutional neural module is used to extract the spatial information of the input signal data. In addition, the total number of parameters of the global model is reduced by weight sharing to reduce the computational effort. The three convolutional layers can obtain more extensive spatial feature of the signal. The signal processed by the convolution layer can be expressed as

$$S[i,j] = \sum\nolimits_{k=1}^{n_{in}} [X_k * W_k][i,j] + b, \tag{2}$$

where W_k is the ***k-th*** kernel matrix of sub-convolution, X_k indicates the corresponding ***k-th*** input of the model, the bias of CNN is b, and $S[i,j]$ signifies element value of the output matrix.

4 Simulation and Analysis

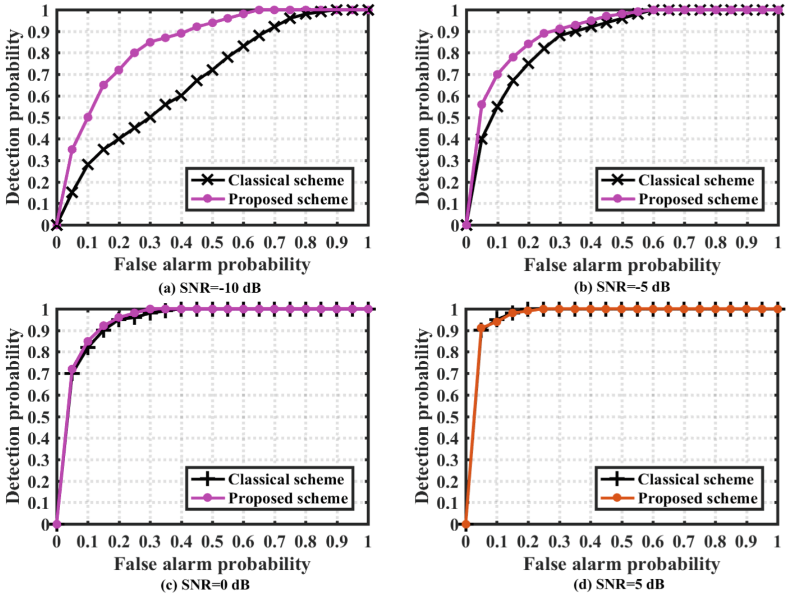

Fig. 2. The accuracy comparisons under various condition.

The parameters used in our simulations are shown in Table 1, the basis of our simulations is the NR-MBMS system described in [4]. We generate experimental data in the simulation platform, which mainly includes the number of users of each base station,

Table 1. The simulation parameters

Parameter	Value
Bandwidth	$B = 100$ MHz
Power	$P_b = 40 \times 10^3$ mW
Slot	$\tau = 1$ ms
Pass loss exponent	$\alpha = 4$
Noise power	$\alpha^2 = 10^{-17.4}$ mW
Rate constraint	$r_1 = 900$ Mbps
Delay constraint	$D_2 = 2.5$ ms
Cell radius	$R = 500$ m
User number of slice 1	$N_1 = 30$
User number of slice 2	$N_2 = 70$

each user's geographical location, the distance between the base station and the user, and the user azimuth obtained from associated based station.

The details of generating data are described as below. The simulation band is performed at ultra-high frequency (VHF), where the setting of carrier frequency is 7.0×10^8 Hz and $fs = 1.6 \times 10^9$ Hz is the receiver sampling frequency. To deal with the subsequent simulation process, first we generate the OFDM signal, and then we add Gaussian white noise to the signal with mean zero and variance 1. Next, we normalize the received signal in terms of energy and estimate the channel state estimation. Finally, the base stations energy efficiency is optimized by jointly allocating the RPM. We calculate the total number of base station traffic data at any given point in time.

5 Conclusion

In this paper, a cascaded CNN-LSTM network is proposed which is able to reckon and forecast the channel state of mobile broadcast users. Also, the RAN slicing function is implemented by using a CNN module to abstract the spatial features of the signal and an LSTM module to extract the temporal features. Then, the spatial and temporal information is integrated into the prediction network based on deep neural networks. In addition, we build a base station model, mainly considering the energy efficiency, and optimize the state information of the channel by using DQN method, and get a better solution. Finally, a simulation study is performed on simulated data to verify the accuracy and efficiency of our proposed algorithm.

References

1. Samdanis, K., Costa-Perez, X., Sciancalepore, V.: From network sharing to multi-tenancy: the 5G network slice broker. IEEE Commun. Mag. **54**(7), 32–39 (2016)
2. Foukas, X., Patounas, G., Elmokashfi, A., Marina, M.: Network slicing in 5G: survey and challenges. IEEE Commun. Mag. **55**(5), 94–100 (2017)
3. Afolabi, I., Taleb, T., Samdanis, K., Ksentini, A., Flinck, H.: Network slicing and softwarization: a survey on principles, enabling technologies, and solutions. IEEE Commun. Surv. Tuts. **20**(3), 2429–2453 (2018)
4. Zhang, S.: An overview of network slicing for 5G. IEEE Wirel. Commun. **26**(3), 111–117 (2019)