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Machine Learning Inspired Code word Selection for Dual Connectivity in 5G User-centric Ultra-dense Networks

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Abstract

In future 5G user-centric ultra-dense networks (UUDN), demands of high data rate and high spectrum efficiency (SE) are effectively met by dual connectivity (DC) technology. However, due to huge increase of base stations (BSs) and mobile users (MUs), it becomes difficult for BSs to quickly and precisely select the code word and provide DC to MUs. Hence, different from some traditional methods, our work aims to improve the network performance using the method of machine learning (ML).

First, we model the random distribution of BSs by homogeneous Poisson point processes (HPPPs), where each MU is served by millimeter-wave (mm Wave) channel. Second, the probabilities that macro cell BS (MBS) or small cell BS (SBS) serves the MU are further derived to get the average sum rate (ASR) in UUDN. Third, inspired by ML, we utilize an iterative support vector machine (SVM) classifier to select the code words of BSs, with sequential minimal optimization (SMO) algorithm used for training all link samples in UUDN.

Then, an iterative SVM-SMO classification (ISSC) algorithm is proposed to achieve a highly efficient performance of DC, where the convergence and complexity are also discussed. The sample training and simulations at last are evaluated by Google TensorFlow. The simulation verified that our proposed algorithm gets a higher ASR than the traditional channel estimation based (CE-based) algorithm. In addition, the results also show a lower computational complexity can be achieved by the proposed algorithm as well.

Index Terms—User-centric ultra-dense networks, dual connectivity, code word selection, machine learning, support vector machine.

I. INTRODUCTION

In the next-generation 5G user-centric ultra-dense networks (UUDN), the mobile user (MU) could use dual connectivity (DC) to improve the transmission rate. Both macro cell base station (MBS) and small cell base station (SBS) simultaneously transmit signals to one MU with the help of millimeter wave (mm Wave) massive MIMO technology. In DC, each base station (BS) selects a code word from a pre-defined codebook to form one directional analog beam to MU, which brings a great performance improvement in downlink transmission of UUDN [1].

DC has already been investigated under different SBS densities before [2], while dynamic DC is further discussed in [3], which leads to a seamless handover of MUs. Those prior works achieve a good enhancement of DC in UUDN. However, with the increasing number of BSs and MUs, it becomes more and more difficulty to use traditional methods [4] to improve the performance, especially for the large random distributed MUs and ultra-dense SBS deployment. Fortunately, AI-based technologies such as machine learning (ML), deep learning (DL), show a very promising way to enhance the wireless performance. Those technologies utilize a large amount of network state information and extract the network features [5]. Based on those features, BSs are able to perform precise judgment such as smart modulation [6], smart channel state estimation [7], and so on. Those previous works significantly lower the calculation complexity, which also show a great potential performance improving for future explosive MUs and SBSs.

II. SYSTEM MODEL

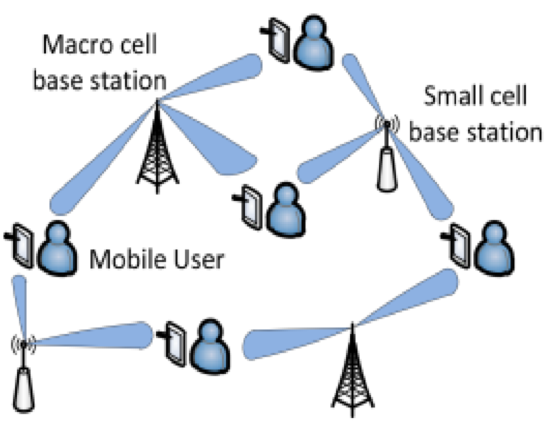

Fig. 1. Scenario Of UUDN With Dual Connectivity

As shown in Fig. 1, we consider a 5G downlink UUDN with the random distribution of MBSs and SBSs. The deployments of both MBSs and SBSs satisfy the HPPPs ΠM and ΠS on two dimensional plane $\mathfrak{R}$ with the density λM and λS, respectively [8], [9]. Every MU, MBS or SBS is equipped with mm Wave massive MIMO, and the number of antenna are defined as NM, BS, NS, BS and NUE, respectively. In our UUDN, the MU supports DC that the downlink transmission can be served by one MBS and one SBS to provide data transmission at the same time [10].

The perfect channel state information (CSI) is supposed to be obtained since we only focus on the process of the code word selection. Each MU adopts the zero forcing (ZF) technique in the downlink baseband process. The wireless traffic is assumed as full buffer. According to Slivnyak's theory, a typical MU can be defined as a downlink receiver in the origin on $\mathfrak{R}$, which does not impact the statistical property of the PPP. With the help of phase shifters before the antennas on each MBS/SBS, a directional analog beam can be transmitted to each MU as Fig. 1 shown.

III. BIG DATA ITERATIVE SVM CLASSIFIER IN 5G UUDN

A. Big data iterative SVM classifier with SMO algorithm

The big data training samples can be obtained based on multiple HPPP snapshots by many times. As we have L propagation paths, there are 2 + 4L random real values as the elements in each training sample, which includes the transmit power, the path loss, 2L azimuth angles of AoA and AoD, 2L real and imaginary parts of the complex gain. Last, each sample in the database is a 1 × (4L + 2) vector xj , j ∈ {1, 2, ..., J}, where J is the total number of the samples in the database. In downlink DC, BS selects one analog beam from NC candidate code words in the codebook.

Without loss of generality, we define U = {c m, cn} ⊂ C, (c m, cn ∈ C), (m≠ n). Denote all the feature vectors which classified to c m are labeled as −1, while classified to c n are labeled as 1. Then, we have the following hyperplane optimization problem:

$$\begin{array}{lll} \min & \frac{1}{2}\|w\|^2 + C\sum_{j=1}^{J}\xi_j & \\ s.t. & y_j\left[w^T\phi(x_j)+b\right] \geq 1-\xi_j & (j \in \{1,2,...,J\}) \\ & \xi_j \geq 0 & (j \in \{1,2,...,J\}) \end{array}$$

B. Iterative SVM-SMO classification (ISSC) algorithm for code word selection

Based on the analysis before, an iteration algorithm is used for classifying all training samples belong to the codebook C, which the output will be the coefficients of all separating hyperplanes. The detail steps of our algorithm are shown as Algorithm 1. In addition, there are NC code words in the codebook C, so 1 2 (NC)2 separating hyperplanes can be obtained with the proposed ISSC algorithm. Then, the MBS/SBS can select the optimal code word by directly referring those separating hyperplanes instead of some traditional methods such as calculating and comparing SNRs or ASRs for all code words

IV. RESULT

Increasing demand of mobile users require high network connectivity and to handle this situation 5G network was introduced and this 5G ultra dense network demand high data rate and spectrum which can handle by Dual Connectivity. 5G network simultaneously access multiple networks at a time to generate fast response which require huge increase of base stations and mobile users, it becomes difficult for BSs to quickly and precisely select the code word and provide DC to MUs. Hence, different from some traditional methods, in this paper author aims to improve the network performance using the method of machine learning (ML). In mobile network each mobile request consist of signal features and this features can be used to identified code words which helps in optimal base station selection. Selected base station will handle mobile request and send response back to client.

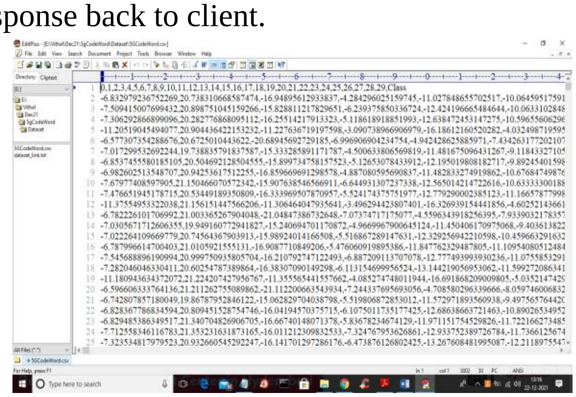

Fig.2 Loaded Dataset

In above screen first row contains signal names and last column contains 'Class' as code words and remaining rows contains signal features. Each row associated with one class label as Code words. SVM-SMO get trained on this signal features and class label and whenever new signal features arrived then SVM will predict Code Word. In below screen we can see names of each code.

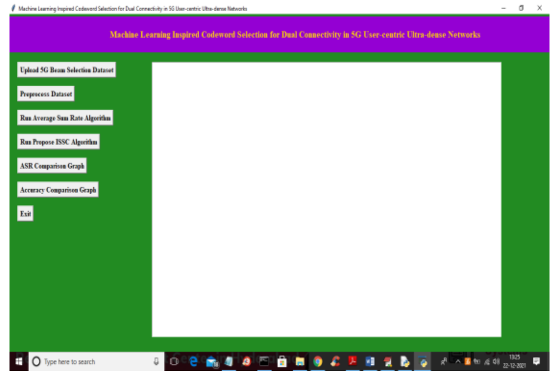

Fig.3 GUI screen for proposed work

In above screen click on 'Upload 5G Beam Selection Dataset' button to upload dataset and to get below screen

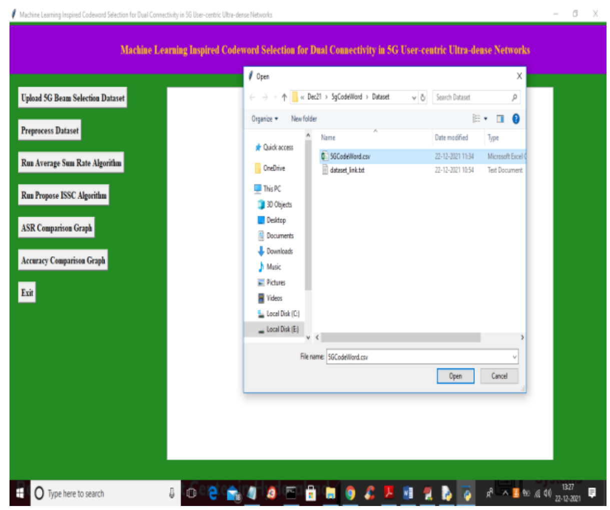

Fig.4 Selection of Dataset file

In above screen selecting and uploading '5GCodeWord.csv' dataset file and then click on 'Open' button to load dataset and to get below screen

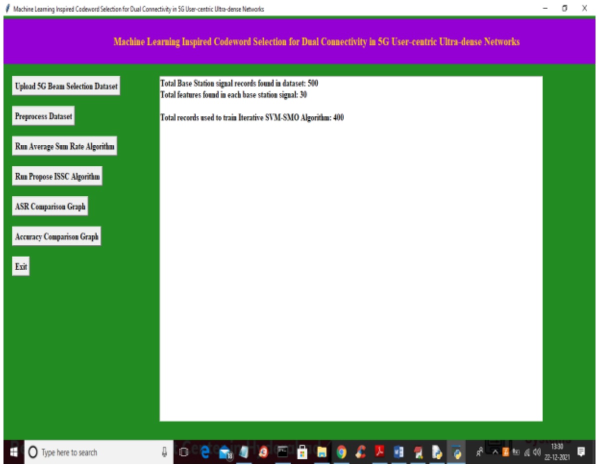

Fig.5 Details of record used

In above screen we can see dataset contains total 500 records and each record contain 30 signal featured and application using 400 records for training and 100 records for testing. Now click on ‘Run Average Sum Rate Algorithm’ button to classify code words based on CHANNEL ESTIMATION using normal SVM algorithm and then calculate ASR rate

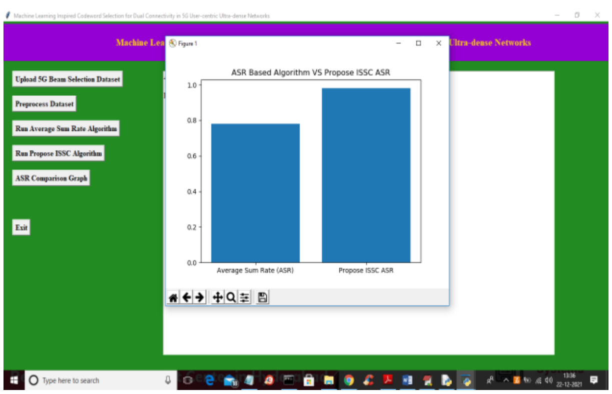

Fig.6 ASR based algorithm vs Proposed ISSC ASR

In above graph x-axis represents algorithm name and y-axis represents ASR values and in both algorithm propose ISSC is giving better ASR correct classification rate.

V. CONCLUSIONS

In this paper, we consider an ML inspired code word selection for downlink DC to improve the ASR of MUs in 5G UUDN. By modeling the random distributions of MBSs and SBSs as HPPPs, we get the expression of receive signal in downlink transmission and further derive the ASR of each MU under DC. Then, we propose an iterative SVM classifier with the data samples include the BS transmit power and channel parameters. With the help of the proposed ISSC algorithm, the separating hyperplanes for code selection in DC can be obtained by data sample training, where both MBS and SBS get a high efficient ASR with very low complexity. In our simulation, the data samples are trained by Google TensorFlow and the results verify that our ISSC algorithm achieves a much closed performance to the theoretical boundary with a significant reduction of calculation complexity.

REFERENCES

[1] U. S. Hashmi, S. A. R. Zaidi, and A. Imran, “User-centric cloud RAN: An analytical framework for optimizing area spectral and energy efficiency,” IEEE Access, vol. 6, pp. 19 859–19 875, 2018.

[2] M. Kamel, W. Hamouda, and A. Youssef, “Performance analysis of multiple association in ultra-dense networks,” IEEE Trans. Commun., vol. 65, no. 9, pp. 3818–3831, 2017.

[3] X. Huang, S. Tang, Q. Zheng, D. Zhang, and Q. Chen, “Dynamic femtocell gNB on/off strategies and seamless dual connectivity in 5G heterogeneous cellular networks,” IEEE Access, vol. 6, pp. 21 359– 21 368, 2018.

[4] J. Cao, T. Peng, Z. Qi, R. Duan, Y. Yuan, and W. Wang, “Interference management in ultra-dense networks: A user-centric coalition formation game approach,” IEEE Trans. Veh. Technol., vol. 67, no. 6, 2018.

[5] Y. Wang, M. Liu, J. Yang, and G. Gui, “Data-driven deep learning for automatic modulation recognition in cognitive radios,” IEEE Trans. Veh. Technol., vol. 68, no. 4, pp. 4074–4077, Apr. 2019.

[6] H. Huang, Y. Song, J. Yang, G. Gui, and F. Adachi, “Deep-learning based millimeter-wave massive mimo for hybrid precoding,” IEEE Trans. Veh. Technol., vol. 68, no. 3, pp. 3027–3032, Mar. 2019.

[7] H. Ye, G. Y. Li, and B.-H. Juang, “Power of deep learning for channel estimation and signal detection in ofdm systems,” IEEE Wireless Commun. Letters, vol. 7, no. 1, pp. 114–117, Feb. 2018.

[8] M. G. Kibria, K. Nguyen, G. P. Villardi, W.-S. Liao, K. Ishizu, and F. Kojima, “A stochastic

geometry analysis of multiconnectivity in heterogeneous wireless networks," IEEE Trans. Veh. Technol., vol. 67, no. 10, pp. 9734–9746, 2018.

[9] M. Haenggi, Stochastic geometry for wireless networks. Cambridge University Press, 2012.

[10] M. A. Lema, E. Pardo, O. Galinina, S. Andreev, and M. Dohler, "Flexible dual-connectivity spectrum aggregation for decoupled uplink and downlink access in 5G heterogeneous systems," IEEE J. Sel. Areas Commun., vol. 34, no. 11, pp. 2851–2865, 2016.