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Deep Learning for Automatic Modulation Recognition: Survey and Discussions

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ABSTRACT

Cognitive radio networks are an innovative approach to wireless engineering in which radios are designed with an unprecedented level of intelligence and agility. This advanced technology enables radio devices to use spectrum (i.e., radio frequencies) in entirely new and sophisticated ways. Cognitive radios have the ability to monitor, sense, and detect the conditions of their operating environment, and dynamically reconfigure their own characteristics to best match those conditions. In this paper we review the modulation recognition in cognitive radio using neural network and other techniques.

Keywords: Cognitive radio, Software-Defined Radio Convolution Neural Network, deep learning technology, automatic modulation recognition.

INTRODUCTION

Nowadays, wireless communication features a settled spectrum assignment policy. With the boosting requirements for wireless band-width of radio spectrum, it’s important to exploit the existing wireless spectrum opportunistically. Without effective measures to regularize wireless spectrum, wireless network will face the serious threat of jamming signals. Hence, people pay more and more attention to improving opportunistic spectrum access techniques, acknowledged as Cognitive Radio (CR). To adjust its parameters to strengthen its ability to reliably communicate, CR are radios that are able to learn their surrounding environment. Currently, wireless spectrum demand is putting spurs to the improved radio efficiency. CR is proposed as one method to be a more open spectrum policy. The famous spectrum assignment policy strategy in CR is Dynamic Spectrum Access (DSA) [12].

Congestion of the radio frequency (RF) environment due to the ubiquity of wireless devices poses new challenges for spectral situational awareness operations. In particular, performing modulation recognition (MR) of known and unknown signals is imperative to make sense of the RF environment. To be useful in real-world applications, MR systems must be: (1) robust to varying signal-to-noise ratios (SNR) and channel conditions; (2) sufficiently general to adapt to signal parameters that may change on-the-fly; and (3) able to provide actionable information on previously unseen signals [6].

Cognitive radio CR is an a enhanced to Software-Defined Radio (SDR) that its automatically detects the surrounding RF, catalysts and smartly accommodates its operating parameters to the infrastructure of network according to meet user demand, if this band is further used by a licensed user, the cognitive radio stirs to other spectrum band or remains in the same band with altering its level of the transmission power or modulation scheme all of that avert interference, calibrations the congestion due to spectrum participating . The main functions for cognitive radios in xG networks can be summarized as follows [15]:

- Spectrum sensing-Spotting unutilized spectrum and sharing the spectrum without disadvantaged interjecting with other users.

- Spectrum management- Captivating the best available spectrum to meet user communication demands.

- Spectrum mobility- Preserving tractable communication exigencies during moving to better spectrum.

- Spectrum sharing- Providing an equitably spectrum scheduling method between cohabitation xG users.

The rest of this paper is organized as follows in the first section we describe an introduction of about cognitive radios. In section II we discuss about the characteristics of cognitive radio, In section III we discuss about the deep learning for cognitive radio. In section IV we present the related work and finally in section V we conclude and discuss the future scope.

II CHARACTERISTICS OF COGNITIVE RADIO

Characteristics of cognitive radio are the capability and reconfigurability which are described in detail as follow:

Cognitive capability-The cognitive capability of a cognitive radio enables interaction with its environment in real time to determine the suitable communication parameters and adapt the radio environment dynamically. The required mission for adaptive operation in open spectrum is shown in Figure 1 which is called as the cognitive cycle.

And the main steps of the cognitive cycle as following:

Spectrum sensing-A CR monitors the available bands on the spectrum and detects the spectrum holes by capturing their information [13].

Spectrum analysis-A CR estimates the properties of these bands which were detected in spectrum sensing.

Spectrum decision-A CR calibration the data rate, the bandwidth, and the mode of transmission, then the fitted spectrum bands are chosen according to the user demands and spectrum properties [9].

Self-organized capability-Spectrum/radio resource management to ably administer and structuring spectrum bands information among secondary users, good spectrum management scheme is needful. Connection and mobility management due to disparate of XG networks, routing and topology information is more complicated but its help to discover the neighbourhood, available Internet access can be detected and the vertical handoffs can be supported which aid secondary users to choose route and networks.

Trust/security management- Since CRNs are disparate networks in complexion, various heterogeneities (e.g., system/network operators, wireless access technologies) offers amount of security tasks. Trust is thus a persecution for securing processes in CRNs.

Cognitive re-configurability-Reconfigurability is the calibre of adjusting the parameters of operating for the transmission on the fly without changing on the hardware components. This ability enables the CR to dynamically adaptation with the radio environment [11].

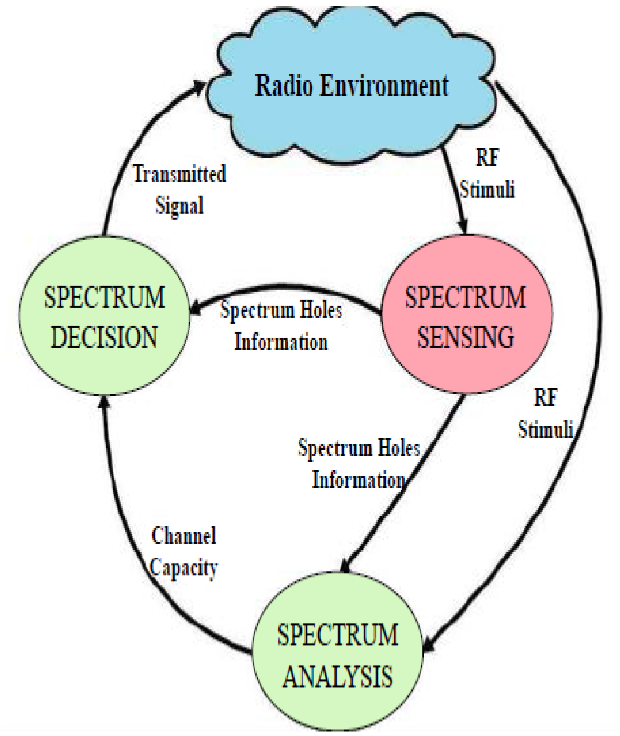

Fig 1: Cognitive radio cycle architecture.

III DEEP LEARNING FOR AUTOMATIC MODULATION RECOGNITION

Wireless communication engineers have been adapting the latest deep learning technology to signal recognition. Several works have been focusing on applying DL to AMR scenarios. Azzous, who were pioneers in this field, proposed using an artificial neural network (ANN) to classify analog modulated communication signals. This attempt inspired the idea of applying deep learning to AMR. O'Shea proposed a method for applying a Convolutional Neural Network (CNN) to the field of modulation recognition, by using the time domain in-phase and quadrature (IQ) signal as the input to the network. For the first characteristic, most of the existing independent studies analyzed the supervised learning scenario. These studies explored the impacts of network structure and signal representation on classification results. They have achieved good results in this scenario. However, most of these efforts were conducted with ideal amounts of training data. They did not explore the use of AMR methods when missing labelled training data. These problems are more likely to occur when dealing with unknown tasks and signals, such as signal acquisition in non-cooperative situations. Additionally, Tang Bin applies GAN as an approach of data augmentation. But in essence, it is based on sufficient amount of labelled data. Regarding the second characteristic, most of the existing methods are carried out by extracting features firstly and then performing classification. This approach is not fundamentally different from traditional expert-knowledge-based modulation recognition, except that the deep neural network is regarded as an enhanced classification tool. In the realization of cognitive radio, this limited the ability of systems to adapt to unknown and new tasks.

IV RELATED WORK

[1] In this paper author proposed a deep learning based method, combined with two convolutional neural networks (CNNs) trained on different datasets, to achieve higher accuracy AMR. A CNN is trained on samples composed of in-phase and quadrature component signals, otherwise known as in-phase and quadrature samples, to distinguish modulation modes, which are relatively easy to identify. They adopted dropout instead of pooling operation to achieve higher recognition accuracy. A CNN based on constellation diagrams is also designed to recognize modulation modes that are difficult to distinguish in the former CNN, such as 16 quadratic-amplitude modulations (QAM) and 64 QAM, demonstrating the ability to classify QAM signals even in scenarios with a low signal-to-noise ratio. [2] In this paper, author proposed a robust spectrum sensing framework based on deep learning. The received signals at the secondary user's receiver are filtered, sampled and then directly fed into a convolutional neural network. Although this deep sensing is effective when operating in the same scenario as the collected training data, the sensing performance is degraded when it is applied in a different scenario with different wireless signals and propagation. They

incorporated transfer learning into the framework to improve the robustness. Results validate the effectiveness as well as the robustness of the proposed deep spectrum sensing framework. [3] In this paper, author considered one of the problematic issues of creating radio systems based on cognitive radio technology, viz., and automatic recognition of the digital-modulation formats of radio signals. In accordance with the recommendations of the E2R and the European Telecommunications Standards Institute (ETSI) consortium, cognitive radio systems have the ability to modulate/demodulate signals in all frequency bands and in all modes of modulation. This process should be performed automatically, according to the current technical capabilities of the available communication system, the requirements for the quality of communication, and different external conditions. This article provides an analysis of the promising methods of automatic recognition of digitally modulated radio signal formats, viz., using the shape of the phase constellation, using the distribution difference of instantaneous phases, and using high-order cumulants. According to the results of the analysis, they proposed methods of recognition that are based on cumulant analysis for cognitive radio systems. It is proposed that the decision-making device be an artificial neural network. [4] In this work, we present an improved algorithm for blind modulation recognition of digital and analog modulated signals in cognitive radio (CR). We provide two different decision trees, one that exploits higher order moments, the other one that is based on signals features. The scheme we propose first identifies which modulation the signal belongs to (e.g. amplitude, phase, or frequency modulated signal), and then recognizes (in case of digitally modulated signals) the number of levels of the modulation itself. Our algorithm recognizes the following signals, (i) analog modulations: FM, AM, SSB (LSB and USB); (ii) digital modulations: BPSK, QPSK, 8PSK, 16PSK, 4ASK, 2FSK, 4FSK, GMSK, 8QAM, 16QAM, 32QAM, 64QAM. The simulation results show the superiority of our approach, thus confirming the effectiveness of our method for the correct classification of the modulation types of CR signals. [5] In this paper, author proposed a novel hybrid radio resource allocation management control algorithm that integrates multi-objective reinforcement learning and deep artificial neural networks. The objective is to efficiently manage communications system resources by monitoring performance functions with common dependent variables that result in conflicting goals. The uncertainty in the performance of thousands of different possible combinations of radio parameters makes the trade-off between exploration and exploitation in reinforcement learning (RL) much more challenging for future critical space-based missions. Thus, the system should spend as little time as possible on exploring actions, and whenever it explores an action, it should perform at acceptable levels most of the time. The proposed approach enables on-line learning by interactions with the environment and restricts poor resource allocation performance through 'virtual environment exploration'. Improvements in the multi objective performance can be achieved via transmitter parameter adaptation on a packet-basis, with poorly predicted performance promptly resulting in rejected decisions. Simulations, presented in this work, considered the DVB-S2 standard adaptive transmitter parameters and additional ones expected to be present in future adaptive radio systems. Performance results are provided by analysis of the proposed hybrid algorithm when operating across a satellite communication channel from Earth to GEO orbit during clear sky conditions. The proposed approach constitutes part of the core cognitive engine proof-of-concept to be delivered to the NASA Glenn Research Centres SCaN Testbed located onboard the International Space Station. [6] In this paper, author outlined the core components of a modulation recognition system that uses hierarchical deep neural networks to identify data type, modulation class and modulation order. Their system utilized a flexible front-end detector that performs energy detection, channelization and multi-band reconstruction on wideband data to provide raw narrowband signal snapshots. They automatically extracted features from these snapshots using convolutional neural network layers, which produce decision class estimates. Initial experimentation on a small synthetic radio frequency dataset indicates the viability of deep neural networks applied to the communications domain. [8] In this paper, author introduced the generative adversarial network (GAN) into the radio machine learning domain. Modulation recognition is performed by a general, scalable, end-to-end framework. The concept of a GAN was first proposed by Goodfellow in 2014. A GAN consists of a generator network that produces samples from code, and a discriminator network that distinguishes real samples from fake ones. These two networks play a min-max game which improves the performance of both networks. GAN have been proven to be especially powerful tool in computer vision and image processing because of its ability to expand datasets for semi-supervised learning. Author wanted to introduce this capability into the field of modulation identification. [9] In this paper, an EE+SE tradeoffs based target is considered for the primary users (PUs) and the secondary users (SUs). First of all, considering the orthogonal frequency division multiple access (OFDMA)-based resource allocation (RA) for the underlying SUs, author formulated an objective function through minimizing a weighted sum of the secondary interference power, where the network performance of both PUs and SUs are guaranteed by the constraints on quality of service (QoS), power consumption and data rate. However, it is a NP-hard problem. In order to solve it, they proposed a damped three dimensional (D3D) message-passing algorithm (MPA) based on deep learning. Specifically, a feed-forward neural network is devised and an analogous back propagation (ABP) algorithm is developed to learn the optimal parameters of the D3D-MPA. To improve the computational efficiency of the allocation and the learning, a suboptimal RA scheme is deduced based on a damped two dimensional (D2D) MPA. Finally, simulation results are provided to confirm the effectiveness of their proposed scheme. [10] In this paper, author proposed a deep learning-based AMC method that employs Spectral Correlation Function (SCF). In our proposed method, one deep learning technology, Deep Belief Network (DBN), is applied for pattern recognition and classification. By using noise-resilient SCF signatures and DBN that is effective in learning complex patterns, they achieved high accuracy in modulation detection and classification even in the presence of environment noise. Their simulation results illustrate the efficiency of their proposed method in classifying 4FSK, 16QAM, BPSK, QPSK, and OFDM modulation techniques in various environments. The method, author proposed, was an SCF pattern based AMC method that employs a deep learning technology, Deep Belief Network (DBN) that is used for identifying different modulation techniques. By using DBN it is possible to abstract the complex features of the modulation techniques that are represented by the associated SCF patterns. By doing so, their proposed method is able to distinguish different modulation methods. As illustrated in the simulation results, their proposed method is highly resilient to the environment noise.

V CONCLUSION AND FUTURE SCOPE

Wireless communication is one of the fastest growing areas of communication in the past decade. In recent years, there is a drastic increase in a number of users, which results in increased demand for radio spectrum increase proportionally. Energy efficiency (EE) and spectrum efficiency (SE) have received significant attentions on optimizing the network performance in cognitive radio networks. In the previous author author used the deep learning model for the cognitive radio network in future we used some other neural network model and techniques to improve the performance of network.

REFERENCES:-

[1] Yu Wang, Jie Yang,, Miao Liu, “Data-Driven Deep Learning for Automatic Modulation Recognition in Cognitive Radios”, IEEE TRANSACTIONS ON VEHICULAR TECHNOLOGY, VOL. 68, NO. 4, APRIL 2019, pp 4074-4077.

[2] Qihang Peng, Andrew Gilman, Nuno Vasconcelos, Pamela C. Cosman, and Laurence B. Milstein, "Robust Deep Sensing Through Transfer Learning in Cognitive Radio",Arxiv 2019, pp 1-4.

[3] S. S. Adjemova, N. V. Klenova,b, M. V. Tereshonoka, and D. S. Chirov, "Methods for the Automatic Recognition of Digital Modulation of Signals in Cognitive Radio Systems", Moscow University Physics Bulletin, 2015, Vol. 70, No, pp. 448–456.

[4] F. Benedetto, A. Tedeschi, G. Giunta, "Automatic Blind Modulation Recognition of Analog and Digital Signals in Cognitive Radios", IEEE 2016, pp 1-5.

[5] Paulo Victor R. Ferreira, Randy Paffenroth, Alexander M. Wyglinski, Timothy M. Hackett, Sven G. Bilenz, "Multi-Objective Reinforcement Learning–based Deep Neural Networks for Cognitive Space Communications", IEEE 2017, pp 1-8.

[6] Krishna Karra, Scott Kuzdeba, and Josh Petersen, "Modulation Recognition Using Hierarchical Deep Neural Networks", IEEE International Symposium on Dynamic Spectrum Access Networks 2017, pp 1-3.

[7] WOLFGANG KELLERER, PATRICK KALMBACH, MARTIN REISSLEIN, "Adaptable and Data-Driven Softwarized Networks: Review, Opportunities, and Challenges", IEEE 2019, pp 1-21.

[8] Mingxuan Li, Ou Li, Guangyi Liu and Ce Zhang, "Generative Adversarial Networks-Based Semi-Supervised Automatic Modulation Recognition for Cognitive Radio Networks",MDPI 2018, pp 1-22.

[9] Miao Liu, Tiecheng Song, Jing Hu, "Deep Learning-Inspired Message Passing Algorithm for Efficient Resource Allocation in Cognitive Radio Networks", IEEE 2018, pp 1-13.

[10] Gihan J. Mendis, Jin Wei, Arjuna Madanayake, "Deep Learning-Based Automated Modulation Classification for Cognitive Radio", IEEE 2016, pp 1-6.

[11] Francisco Paisana, Ahmed Selim, Maicon Kist, Pedro Alvarez, "Context-Aware Cognitive Radio Using Deep Learning", IEEE International Symposium on Dynamic Spectrum Access Networks 2017, pp 1-2.

[12] Bin Tang, Ya Tu, Shaoyue Zhang, Yun Lin, "Digital Signal Modulation Classification with Data Aug-mentation Using Generative Adversarial Nets in Cogni-tive Radio Networks",IEEE Access, pp 10-19.

[13] M. Venkata Subbarao and P. Samundiswary, "Spectrum Sensing in Cognitive Radio Networks Using Time–Frequency Analysis and Modulation Recognition", Springer 2018, pp 827-837.

[14] Tianqi Wang, Chao-Kai Wen, Hanqing Wang,, Feifei Gao, Tao Jiang4, Shi Jin, "Deep Learning for Wireless Physical Layer: Opportunities and Challenges", China Communications November 2017, pp 92-111.

[15] Rayan Abdelazeem Habboub Suliman, Khalid Hamid Bilal and Ibrahim Elemam, "Review Paper on Cognitive Radio Networks Rayan Abdelazeem", Electrical Electron System 2018, pp 1-3.

[16] Dinu Mary Alias, Ragesh G. K, "Cognitive Radio Networks: A Survey", IEEE 2016, pp 1981-1986.

[17] Zeinab Imadeldin Abasher Mohamed Ahmed, Dr. Khalid Hamid Bilal, Dr. Mustafa Mohamed Alhassan, "Cognitive Radio Network Review", IJEAM 2016, pp 19-27.

[18] Tim O'Shea, Jakob Hoydis, "An Introduction to Deep Learning for the Physical Layer", IEEE 2017, pp 1-13.

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