Artificial Intelligence Enabled Radio Propagation for Communications—Part I: Channel Characterization and Antenna-Channel Optimization

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I. ABSTRACT

To provide higher data rates, as well as better coverage, cost efficiency, security, adaptability, and scalability, the 5G and beyond 5G networks are developed with various artificial intelligence (AI) techniques. In this two-part article, we investigate [1] the application of AI and, in particular, machine learning (ML) to the study of wireless propagation channels. It first provides a comprehensive overview of ML for channel characterization and ML-based antenna–channel optimization in this first part, and then, it gives a state-of-the-art literature review of channel scenario identification and channel modeling in Part II. Fundamental results and key concepts of ML for communi- cation networks are presented, and widely used ML methods for channel data processing, propagation channel estimation, and characterization are analyzed and compared. A discussion of challenges and future research directions for ML-enabled next- generation networks of the topics covered in this part rounds off this article.

***Index Terms*—Human Resource, Competence, Training Programs, APQP (Advanced Product Quality Planning) , Information Management, QMS (Quality Management System), Skill Analysis, Learning Management, Customer Relationship Management (CRM), Database Management**

II. INTRODUCTION

HE dramatic increase of the numbers of wireless users and wireless applications brings new demand and chal- lenges for wireless comm [2]unication networks. The 5G and beyond 5G (B5G) networks are expected to provide higher data rates, as well as better coverage, cost efficiency, security, adaptability, and scalability. Since 2020, 5G commu- nication has begun to be deployed worldwide, whereas studies of sixth-generation (6G) wireless communication net- works have started in academic and industrial research labs to further enhance MBB, expand the application and coverage of the Internet of Things (IoT), and make networks/devices more intelligent. These new application scenarios give the 6G network a series of new performance requirements: 10–100 million devices connections [3] with the peak data rate of 1–10 TB/s; the mobility that needs to be supported rises to higher than 1000 km/h to accommodate ultrahigh-speed train (uHST), unmanned aerial vehicle (UAV), and satellites; latencies need to be reduced to fractions of 1 ms to account for tactile Internet and other real-time control applications; and reliability of five or even seven times has to be achieved for mission-critical applications. Also, to provide global coverage, 6G wireless networks will expand from terrestrial communication networks to space–air–ground–sea integrated networks. The study of propagation channels is a fundamental aspect of any wireless communication system design, network optimization, and performance evaluation. Therefore, to realize 6G networks to meet the requirements above, the corresponding wireless channels need to be thoroughly studied. However, the massive—in terms of number of devices, number of antennas, bandwidth, and so on— scenarios not only pose a challenge in performing dedicated measurement campaigns but also lead to massive amounts of data that need to be processed and analyzed . Classical techniques for such analysis, e.g., parameter estimation, tracking, clustering, and characterization, are generally less suited for such large amounts of data, either because of the resulting overhead or because they might miss important relationships within the data. On the other hand, artificial intelligence (AI) has been developed to "simulate the human intelligence [4] processes by machines, especially computer systems" . Machine learning (ML) is a branch of AI that enables machines to learn from a massive amount of data and make decisions and/or perform actions accordingly without being given any specific commands. With the help of continually increasing computing power, ML techniques have achieved great success in big data processing for many applications, e.g., image processing, natural language processing, and data mining. Consequently, ML techniques have also been widely applied to various problems in communications networks and are expected to be an integral part of next-generation communication networks.

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III. AI-/ML-A SSISTED O PTIMIZATION AND M ODELING FOR A NTENNA D ESIGN TO I MPROVE R ADIO P ROPAGATION

he simplest method to use channel information to adapt antenna properties for improved antenna–channel interaction is to rely on an antenna array to provide different spatial properties of the antenna system. Specifically, one can select between a finite set of spatial filters, made possible by either turning on/off different antenna elements (in the case of transmit antenna selection (TAS) ,fixed beams, or antenna tilt, selecting different preformed beams covering the horizontal plane, or steering the beam in elevation. In a generic sense, this approach is about connecting the antenna array outputs to the transmitter or receiver through a beamforming network, where the array weights can be set according to the desired selection functionality.

a) : Among these applications, TAS has received the most attention in the literature , due to the topic being of interest since the early days of multiantenna systems. The basic idea of TAS is to devise an algorithm to select P out of MT transmitting antennas (P ¡ MT) to be connected to the RF chains such that the best possible end-to-end link performance is achieved. This technique is motivated both by the reduced hardware cost due to the need for fewer RF chains and the modest loss of performance under some conditions.

b) : The interest in applying ML to TAS is not limited to single- user MIMO, but it has also been considered for multiuser massive MIMO systems . In , the self-supervised learning-based Monte Carlo tree search (MCTS) method is proposed to solve the antenna selection problem using channel capacity as the key performance indicator. The components in the TAS system model are mapped to the basic elements of MCTS (action, tree state, and reward). Linear regression is used to obtain channel features and provide prediction to MCTS, facilitating the self-supervised learning process. Simulation results show high search efficiency with near-optimal performance, with the BER performance giving a 1 dB gain over the greedy search selection method. The proposed method also achieves a similar near-optimal BER performance as the search-based branch and bound (BAB) method, but with 50

IV. Computer Vision-Based Cluster Identification

Computer Vision-Based Cluster Identification: Before automatic cluster identification methods were devised, MPC clusters were identified by human inspection as in, [5]. Despite the somewhat subjective operation model in human-eyeball clustering, there are still some basic criteria that are generally applied, including the shape of the potential cluster, the distribution pattern of the MPCs' delay and angle, and the power distribution of all MPCs. All these principles are visual-based, and hence, it is also possible to use an image processing method to recognize the MPC cluster. Inspired by this, some studies focus on computer vision-based cluster identification. With the consideration of the delay behaviors

Category	Typical Algorithm	Parameter Type	Existing Works
Traditional Mehod	Barlett A	PAS	[62]
Traditional Mehod	ESPRIT	Signal angle	[63]
Traditional Mehod	SAGE	MPC Joint	[64]
Traditional Mehod	RiMAX	DMC	[65]
Traditional Mehod	SVM	Path Loss	[66]
ML-based method	ANN	Channel escess	[67]
ML-based method	SVM-PCA	AoA and ASA	[68]
ML-based method	Bayesian Learning	DoA	[69]
ML-based method	RVM C	DoA	[70]
ML-based method	EKF	MPC Joint	[71]

TABLE I
SUMMARY OF CHANNEL PARAMETER ESTIMATION

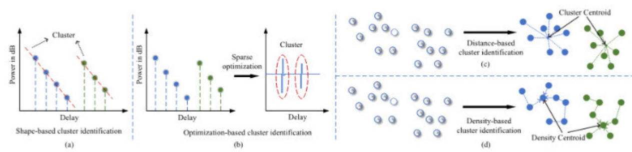

Fig. 1. Example Image

of the MPCs, a Hough transform-based clustering algorithm is present in for vehicle-to-vehicle (V2V) channels, which exploits the Hough transform [1] to recognize the trajectory of MPC in the delay domain and merges the recognized trajectory into clusters. A PAS-based clustering and tracking (PASCT) algorithm without any high-resolution parameter extraction is proposed in; it introduces the maximum-between-class-variance method to sepa- rate the potential cluster groups from the background noise and further divides the clusters by using the density-peak-search method . The PASCT algorithm identifies the clusters directly from the PAS, which can be fast obtained by applying the Bartlett beamformer. A similar method is also adopted in , where the cluster is recognized from the PAS by using image denoising, coarse-grained seg- mentation, and fine- grained segmentation. The vision-based cluster identification follows an intuitive approach and thus can provide identification results that conform to human ob- servation and benefit from the rapid development of computer vision science.

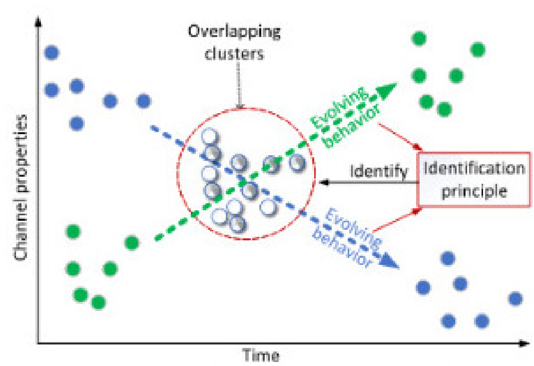

Fig. 2. Illustration of the evolving-based cluster identification

In summary, the ML-based cluster identification solutions show a significant ability to identify the MPC clusters for further analyzing and modeling, and each identification solution has its own advantages and limitations. Considering that there is no identification ground truth of the measurement data, how to properly quantify the performance of the identification method is still a challenging issue. [6]One way is by evaluating the identification method by using synthetic data generated from a cluster-based channel model, where the identification ground truth of the synthetic data can be easily acquired. Another solution is to use the statistical figure of merits for data clustering algorithms, e.g., the Calinski–Harabasz index , generalized Dunn's (GD) index, Xie–Beni (XB) index , or Davies–Bouldin index . Several measuring methods, including the indices above, are compared in , where the XB index and GD index generally show good performance for evaluating the MPC cluster identifi- cation result. Table III summarizes the existing clustering methods for wireless channels.

V. ML-Based Beam Selection and Antenna Tilt Optimization

Using ML to determine antenna tilt for coverage and interference optimization is also a popular subject in the literature . In simple terms, a suitable antenna tilt can improve signal reception within a cell and reduce interference toward other cells, leading to a higher signal-to- interference-plus-noise ratio (SINR) received by the users and increased sum data rate in the network. However, the traditional fixed-tilt strategy is not adequate for the complex coverage and interference problem in heterogeneous networks (HetNets). In [7] a distributed reinforcement learning algorithm is proposed, which does not need a base station or network-wide knowledge of hotspot locations. In the simula- tion results in that paper, the Boltzmann exploration algorithm can achieve convergence to a near-optimal solution within limited iterations and improve the throughput fairness by 45 56 fixed strategies. It is shown in that distributed rein- forcement learning is also attractive for the antenna tilting for self-optimization of the RAN, even for homogeneous networks. Simulation results show a 30 rate in an urban scenario when the tilt angle is optimized

VI. Data-Driven Design of Antenna Patterns

To benefit more from channel information than aiding in the selection of antenna/beam/tilt, the channel data can be more directly utilized in optimizing antenna–channel interaction to improve system performance. Since [8]optimizing For cluster recognition/extraction, most of the existing works rely on unsupervised clustering algorithms, e.g., K-means or fuzzy-C-means. However, the unsupervised algo- rithms generally rely on preset parameters, e.g., the number and the position of initial cluster-centroids. Thus, the current clustering algorithm requires different presettings for different channel data, which requires extensive manual adjustment to maintain the clustering accuracy for nonstationary channels. On the other hand, the ANN-based DL shows great flexibility for the applications of target recognition and has already been extended to solve the clustering problem , which is highly related to the MPC's cluster recognition. Neverthe- less, the accuracy of the DL-based cluster recognition is not increased as expected compared to the existing unsupervised clustering methods. Therefore, it requires more studies on how to further improve the accuracy and efficiency of the DL-based clustering methods. At the same time, the possibility of tracking joint clustering of time-varying MPCs also requires further investigation.antenna–channel interaction is mainly about "far-field match- ing," one can design the antenna pattern for some desired properties

VII. DL-Based Cluster Identification

For cluster recognition/extraction, [9] most of the existing works rely on unsupervised clustering algorithms, e.g., K-means or fuzzy-C-means. However, the unsupervised algorithms generally rely on preset parameters, e.g., the number and the position of initial cluster-centroids. Thus, the current clustering algorithm requires different presettings for different channel data, which requires extensive manual adjustment to maintain the clustering accuracy for nonstationary channels. On the other hand, the ANN-based DL shows great flexibility for the applications of target recognition and has already been extended to solve the clustering problem , which is highly related to the MPC's cluster recognition. Nevertheless, the accuracy of the DL-based cluster recognition is not increased as expected compared to the existing unsupervised clustering methods. Therefore, it requires more studies on how to further improve the accuracy and efficiency of the DL-based clustering methods. At the same time, the possibility of tracking joint clustering of time-varying MPCs also requires further investigation.

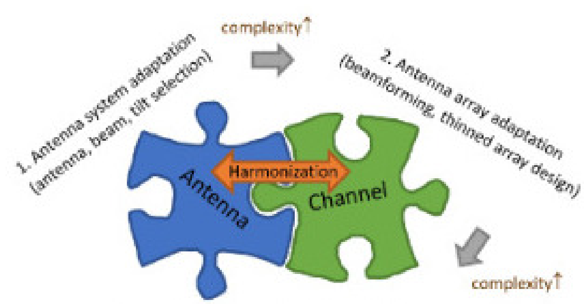

Fig. 3. Example Image

VIII. AI-Based Applications for mmWave/THz-Band Communications

Channel measurements [10] (especially in mmWave and THz band) are often accompanied by maddening time consumption, engineering problems, and capital costs. The ML method needs training data, and reliable training data should come from the measurements in actual scenarios. In this sense, data acquisition is the bottleneck of many ML-based applications. Admittedly, some simulation methods can generate synthetic training data, but the simulation methods themselves also need measurement data for evaluation and verification. Hence, con- ducting sufficient measurement campaigns to support AI-based applications is one challenging aspect in the future for mmWave/THz channels. Meanwhile, the mmWave/THz chan- nels with the ultrawideband and ultramassive MIMO have shown some new properties, e.g., channel sparsity, chan- nel hardening, and nonstationarity in time/spatial/frequency domains. These new channel properties may significantly affect channel data processing and have not been considered yet in the existing AI-based applications, e.g., channel sparsity property may contribute to cluster identification; channel hard- ening may improve the scenario identification. How to exploit new channel properties to improve the efficiency, accuracy, and robustness of AI-based applications in communications still requires further investigation

IX. Conclusion

AI techniques have become a necessary tool to develop the next-generation communication network. In this arti- cle, we provide a comprehensive overview of AI-enabled data processing for propagation channel studies, includ- ing channel parameter estimation and characterization and antenna–channel optimization in Part I, whereas the scenario identification and channel modeling/prediction are covered in Part II . This article demonstrates the early results of the related works and illustrates the typical AI/ML-based solutions for each topic. Based on the state of the art, the future challenges of AI/ML-based channel data processing techniques are given as well.

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