Enhancing Wave Propagation via Contextual Beamforming

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***Abstract*—Beamforming is a cellular base station traffic-signaling system that determines the most effective data-delivery path for a specific user while reducing interference for neighboring users, and it has now become an integral technology in modern wireless communication systems. Contextual beamforming has evolved as an intelligent method in which the location information of a mobile user is predicted based on prior knowledge, and subsequently reconfigure the antenna arrays. Such a system relies heavily on a machine and deep learning applied on the data gathered to infer the context. This paper presents an antenna beamforming approach that exploits the location information of a moving mobile user in a mobile network. Our results show that network parameters such as the received power and propagation path information can assist to construct a machine learning-based adaptive beamforming framework.**

Keywords—Antenna Array Beamforming; Contextual Beamforming; Massive MIMO; Machine Learning

I. Introduction

In cellular commutations, a mobile user experiences the effects of handoff or handover that happen when a user passes from one base station (BS) to another. In this scenario, the frequencies in adjacent cells are not reused to prevent interference. The antennas used at the BS not only contribute a very high computational overhead but also reduces energy efficiency. Highly directional antennas which are going to be a key component of future wireless networks such as the millimeter wave (mmWave) systems enable us to improve the network efficiency by reducing interference. The high gain directional antennas with multi-beam techniques improve coverage, robustness, and non-line of sight (NLoS) operations. Moreover, the incorporation of smart, closed-loop algorithms with these antennas determines the most promising signal paths with fast switching within and across access points or user equipment [1]. In this regard, localization i.e., the ability to predict the mobile user's next spatial position based on its historical motion can be exploited to develop smart applications. The development of techniques for approximating and anticipating the receiver's future position allows for the advancement of location forecasting applications and services. In general, a wireless device controls a location-predicting system by collecting and supplying the requisite data before the application. The sender must be capable of determining the receiver's location at any given time in order to communicate efficiently with the receiver. The concept of using machine learning (ML) to predict the receiver's position has already been proven [1]. The receiver's status data at a given time is reported, analysed, and transcribed as context. Several ML methods, used in addition to Global System for Mobile Communications (GSM), and Global Positioning System (GPS), have been recognised as contributing to the technical development of location forecasting. GPS works well in the line of sight (LoS) scenarios, however, its incapability of working in NLoS and indoor environments calls for the need to predict the location base on prior information. Furthermore, the advances in electronic devices have enabled us to perform quite complex computation in near real-time. Different algorithms can be used according to the requirement, for example, some algorithms exploit location out of the physical movement, while others infer from the channel state information (CSI). Depending on the application, ML algorithms can be configured and designed to meet its needs [1]. Beamforming acts as a signalling system for cellular networks. Instead of broadcasting in an omnidirectional fashion, it allows a BS to transmit a focused beam to a specific user [2]. This spatial precision prevents interference, and therefore, a particular BS can handle more incoming and outgoing data streams at a given time. Despite all the advancements, fifth-generation communications and particularly mmWave systems pose huge challenges to developing an efficient network, and chief among them is the extremely small spatial coverage. Moreover, the coexistence of multiple wireless technologies also introduces additional constraints. Conventional beamforming can be done by static, dynamic, transmit, analog, digital or hybrid according to the application.

II. Contextual Beamforming

In the networking industry, predicting an object's future position has proven difficult. Because of its wide use in a variety of fields, location forecasting has received a lot of attention [1]. As a result of the increased efficiency of beam navigation, the reason for using the beamforming technique is to collect a lower degree of interference with higher strength. Beamforming is a type of spatial filtering in which a suitable signal receptor corresponds to a group of antennas that can be used to steer transmitted signals in a specific direction [2]. To achieve effective communication and monitoring, various methods and technologies for focusing beam emissions

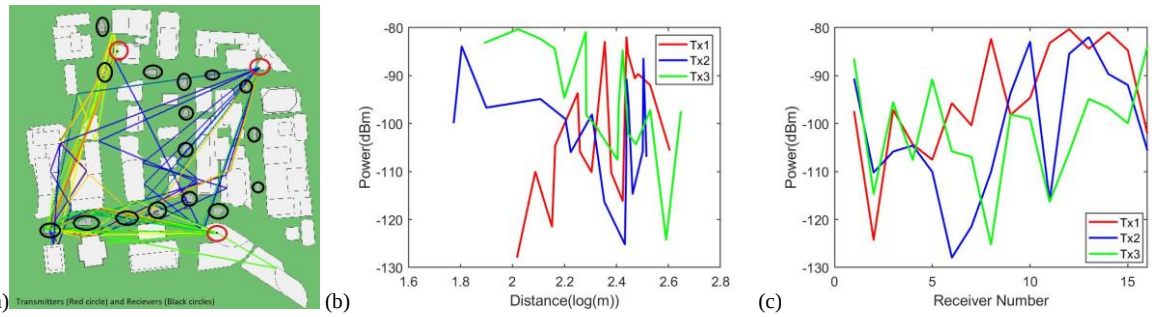

Fig. 1(a) Propagation paths of 3 Transmitters to 1st receiver in vehicular ray tracing scenario in Rosslyn, Virginia. (b) Received power vs Distance. (c) Received power vs Receivers.

towards the receiver direction have been developed [3]. The most popular strategies for directing the projection of the beam, whether in analog or digital mode, are time-delay shift (time delay) and phase shift. By altering the time delay, which is independent of the steered frequency and bandwidth, the time delay method may shape and control the beam. In this context, contextual beamforming in which location information is predicted in advance with help of deep learning-based networks that work on a test (prior collected data) and train data (predicted data) aids in reducing the computational overhead.

III. Demonstrating Contextual Beamforming

In this section, we demonstrate the process of contextual beamforming by setting up a simulation using Remcom Wireless InSite 3.3.0 (WI) [4]. We utilised an existing profile of the city of Rosslyn city, Virginia, USA [4] and introduced different transmitters and receiver routes (considered as a vehicle on move). We consider a scenario where a moving vehicle (on mobile receivers Rx1 to Rx16) communicates with 3 cellular BSs (Tx1, Tx2, and Tx3) (red circled) as illustrated in Fig. 1. All the BS nodes use vertical short dipole antennas that are excited with a carrier frequency of 3.4 GHz and an effective bandwidth of 5 MHz. The BS antenna (Tx1) is placed at a height of 100 m with an offset of 10 m whereas the other two BSs (Tx2 and Tx3) are at 45 m and 70 m with an offset of 4 m and 3 m above 41 m and 67m tall buildings, respectively. All BSs transmit at a power level of 0 dBm. The moving user equipment UE antennas (Rx1 to Rx 16) are placed on the 1 m tall vehicles and 2 m at ground level and takes the indicated route in Fig. 1; this can be implemented in Wireless Insite using the "Points" feature. There exist multiple vehicle locations (points) in the route: some points correspond to the NLoS trajectory and others correspond to the LoS trajectory. Fig. 1(a) indicates the propagation paths to Rx1 from all transmitters. Fig. 1(b) represents the power delivered transmitters to receivers, and Fig. 1(c) shows the power received by each receiver. The power delivered is in the range of -80 dBm to -130 dBm. The fluctuations in the curves are because of NLoS paths to be covered by transmitters. From the ray-tracing simulation, results obtained in terms of received power with respect to distance, path loss, Propagation path, angle of arrival, time of arrival, the direction of arrival, and other parameters can be exported to the algorithm to train the antenna network for location information. There are numerous ML models (such as support vector machine (SVM), convolutional neural network (CNN), gated recurrent unit (GRU), etc.) that can be incorporated with the results obtained from Wireless InSite and generate a self-learned network.

IV. Future Potentials and Conclusion

The design of the beamformers can be done by considering how and where beamforming is needed based on the application. As an example, based on the weight vector application, either fixed weight beamforming or adaptive beamforming can be introduced. Even with adaptive beamforming, we can opt for training or blind methods. In this regard, intelligent antenna systems are of great importance that significantly increases the mobile network performance while reducing co-channel interference. The 'intelligence' of these array antennas stems from the use of adaptive beamforming algorithms to guide the main beam toward the target signal path while rejecting interfering signals of the same frequency from other directions. This is accomplished by updating the weights of each radiating element regularly. This paper proposes the concept of contextual beamforming that exploits the mobile user's current location patterns to configure the antenna beam pattern in the future. The results obtained can be fed to a machine learning framework and a self-learned network for future location estimation can be developed. Future directions of research can involve complex terrains and the use of multiple antennas.

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References

[1] H. Safwat Hasan Hasan, "Beamforming Technique Assisted by Machine Learning Algorithm for Next Location Prediction," *Int. J. Wirel. Commun. Mob. Comput.*, vol. 6, no. 2, p. 37, Feb. 2018, DOI: 10.11648/j.wcmc.20180602.11.

[2] G. Fokin, "Interference Suppression Using Location-Aware Beamforming in 5G Ultra-Dense Networks," in *Proceedings of 2020 IEEE Workshop on Microwave Theory and Techniques in Wireless Communications, MTTW 2020*, Oct. 2020, pp. 13–17, DOI: 10.1109/MTTW51045.2020.9245050.

[3] A. Tall, Z. Altman, and E. Altman, "Multilevel beamforming for high data rate communication in 5G networks," Apr. 2015, Accessed: Apr. 28, 2021. [Online]. Available: http://arxiv.org/abs/1504.00280.

[4] "Remcom." http://stores.modularmarket.com/remcom/digdel_delivery.php (accessed May 07, 2021).