Chapter 1 Introduction

With the continuous advancement of the fifth generation (5G) network construction, whether individual customers or enterprises have increasingly diverse demands for 5G applications. The 5G applications technology has become mature, and its characteristics of minimized end-to-end latency and booming computation capacities at the network edge are constantly being developed to meet the needs of diverse application scenarios. Among them, positioning is recognized as an important application of 5G networks which attracting considerable attention from both academia and industry, and application scenarios such as emergency rescue, internet of vehicles and smart manufacturing have put forward the positioning capabilities whether indoors or outdoors. Therefore, many new techniques for positioning have been investigated and developed due to the specific characteristics of New Radio (NR) positioning and they can work well in both Line-Of-Sight (LOS)and Non-Line of Sight (NLOS)conditions.

The Third-Generation Partnership Project (3GPP) has been one of the main motivators setting standard requirements for 5G positioning. 3GPP proposed NR positioning from Release 16 and implemented as 5G RAT-dependent positioning technology instead of the satellites, the mentioned localization technologies are usually measured based on the timing of the signal or the power of the signal or the angle of arrival/departure of the signal, such as Time of Arrival (ToA), Time Difference of Arrival (TDoA), or Angle of Arrival (AoA). All these technologies are expected to play a significant role in achieving accurate user positioning as they possess desirable attributes, namely large bandwidth, massive antenna arrays, centimeter-wave (cmWave) and millimeter-wave (mmWave) transmissions, among others [1]. Then in the subsequent R17 version that the location capabilities have been enhanced mainly in four aspects by the related studies and technique reports [2-4]: The accuracy enhancement by Timing Error Mitigation (TEM), AOD accuracy enhancement and multipath mitigation, the latency reduction based on the measurement gap and Positioning Reference Signal (PRS) Processing Window, the network efficiency enhancement by using on-demand PRS and the device efficiency enhancement because of the inactive state positioning.

In addition to the traditional cellular-based and enhancement positioning techniques, as artificial intelligence continues to be applied in the field of telecommunications, machine learning assisted positioning in 5G networks has become a new research area that cannot be ignored due to the improvements and enhancements of the positioning performance. In recent years, a large number of studies and reports have shown that no matter what type of machine learning algorithm is used in indoor or outdoor environments, they can achieve a better optimization performance than traditional localization in 5G positioning. In indoor environment, the literature [5] shows supervised learning can improve the performance and to reduce the computation cost of the Wi-Fi indoor localization systems; The literature [6] proposed an unsupervised learning algorithm to train the fingerprints in parallel and made a combination fusion algorithm to improve the accuracy and robustness of indoor localization significantly; The literature [7] proposed a Deep Neural Network (DNN) model to optimized the fingerprint-based 3D positioning and achieved a more accurate positioning result in 5G positioning. In outdoor environments, the literature [8] used 13 machine learning models including Neural Network, supervised and unsupervised learning achieving the minimum error smaller than 3.3m and the simulated results showed the machine learning algorithms and methodologies for employment in DM-MIMO systems can obtain the better positioning performance than traditional localization; The literature [9] also proposed a deep convolutional gaussian processes based regression approach to achieve high robustness for fingerprinting-based mmWave outdoor localization and the simulation results showed it can reach a higher outdoor localization accuracy than a convolutional neural network based baseline method.

The main goal of this paper is to provide a comprehensive overview of machine learning-aided positioning techniques and architectures in 5G networks. To do this comprehensively, we have provided an introduction of the 5G NR physical layer, and an overview of 5G positioning techniques and the localization technologies divided in indoor positioning and outdoor positioning. Then we introduce the machine learning history and various machine learning techniques, such as reinforcement learning and transfer learning. Furthermore, we surveyed the application of machine learning in wireless communication and present the key finding of machine learning limitation and future challenges. At the end of the thesis, we summarized the various utilization of machine learning for 5G positioning based on large number of research and literatures and pointed out the future challenges in machine learning assisted positioning in 5G network based on the properties and limitations of different machine learning algorithms.

The contributions of this paper are the following: Chapter 2 is an introduction to the 5G NR physical layer and the technologies based on the properties – the fundamental technologies used for 5G positioning are summarized here; Chapter 3 is an overview of various machine learning technologies which are widely used in wireless communication and describes the applications utilizing machine learning in wireless communication; Chapter 4 provided an extensive study of machine learning aided positioning techniques in 5G networks according to the properties and advantages we mentioned in above chapters, and the different methods are compared to each other based on the characteristics of positioning. At the end of the paper, chapter 5 concludes this paper and summarize the main findings.

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