INTRODUCTION

BACKGROUND AND CONTEXT

The development of specialized algorithms is an important part of the process of machine learning, which refers to the process by which a computer acquires knowledge (ML). The formation of statistical regularities or particular patterns in the data set used in the study is the most significant feature of learning. Consciousness per se is not the most important aspect of learning. There is an issue with many algorithms that were designed for machine learning since they do not have a good resemblance to how people might learn a task. This is a concern because machine learning is becoming increasingly popular. By applying learning algorithms [1], you are able to improve your comprehension of the ways in which learning could be relatively difficult in a variety of settings. Because the propagation of radio signals is so important to IPS, this necessity served as the driving force for the creation of machine learning (ML) technology. In order for machine learning-reliant systems to function well, they need to gather data pertaining to signal and position, as well as learn about their surroundings and the various patterns that determine how accurately position estimation tasks can be performed [2]. The environment in which positioning systems are used might determine whether they are considered to be indoor or outdoor systems. The process of localization is made more challenging by the fact that the potential for the development of complex infrastructures by the spaces is greater in an indoor setting than it is in an outdoor context. It is possible for spaces to be made more complicated by the inclusion of composite structures such as static and dynamic items, fluctuating physical infrastructure constituting the emplacement, and openings in the internal environment [3].

THE INTELLIGENCE OF ARTIFICIAL SYSTEMS

WHERE DID THE CONCEPT OF ARTIFICIAL INTELLIGENCE COME FROM?

Artificial intelligence is something that has been around for quite some time (AI). John McCarthy, a professor of computer science at Stanford University and the person who initially coined the word, presided over an academic conference on the subject that was held at Dartmouth College the same year. Since that time, the field of artificial intelligence has experienced a number of boom-bust cycles. These cycles were characterized by the discovery of new technological advances, which sparked excitement and activity, but were then followed by a period of disillusionment and apathy known as an "AI Winter." As can be seen in Figure 1, we are currently in the midst of what has been dubbed an "AI Spring." The term "artificial intelligence" refers to computer programs that can imitate human thought processes, as well as copy them, automate them, and even improve upon them. The capacity to see, comprehend, learn, find solutions to problems, and reason are some of the most crucial components of artificial intelligence.

There have been many different definitions of artificial intelligence (AI) proposed over the years, but they all have one thing in common: computers can be programmed to perform human-like functions such as problem-solving, communication, and idea generation. This is the one thing that all of these definitions have in common. In light of this, despite the fact that the processes that lead to AI are considered to be "artificial," the intelligence that AI is designed to emulate can only be compared to that of humans. Because processing inputs from the outside world required extensive programming in the early days of AI research, early AI systems were limited to a relatively small set of inputs and conditions. This was because early AI was still in its infancy. Computer scientists have spent the intervening years working to improve the capabilities of machines that are endowed with artificial intelligence (AI).

Board games are a suitable testing ground for artificial intelligence research because of their constrained number of players, rules, and objectives, as well as their limited number of movements. The human competition in board games like checkers and backgammon and quiz shows like Jeopardy! has been replaced by computer systems. Deep Blue, an IBM chess computer, is renowned for having won a match against the reigning world champion, Garry Kasparov, in 1997. This trajectory continued with the traditional Chinese board game of Go after DeepMind's AlphaGo defeated Lee Sedol in March of 2016. Go is an ancient game. The victory over Sedol was a significant turning point in the evolution of AI. In the past, successful computer programs have been developed using a technique known as the "brute force" approach. In this method, the system first learns the rules of the game, then masters all of the game's possible moves, and finally uses a computer algorithm to determine which move is the most advantageous. Because there are more possible moves on a typical Go board with 19 by 19 lines than there are atoms in the universe, a computer system will never be able to learn all of the possible moves. DeepMind trained AlphaGo to achieve something that human go players have been working on for over 2,500 years: develop a sense of thinking, strategy, and intuition. This is something that DeepMind trained AlphaGo to do in months. The defeat of Lee Sedol by DeepMind's artificial intelligence proves, rather than showing that the AI can learn Go, that it can master anything easier than Go, which covers a wide variety of other activities.

When talking about AI in today's periodicals and mainstream media, it's easy to get lost in the sea of technical jargon and buzzwords that are prevalent in the conversation. Figure 1 illustrates the distinction between artificial intelligence and machine learning, which is necessary knowledge if you wish to understand artificial intelligence.

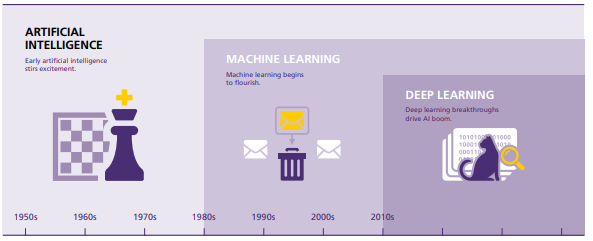


Figure 1: A graphic illustration of AI, deep learning and machine learning is shown in Figure 1.

Machine learning, as opposed to artificial intelligence (AI), which refers to a system or device that is intended to act intelligently, refers to systems that are designed to take in information and learn from it, typically within a defined area. AI refers to a system or device that is intended to act intelligently. These systems are able to form conclusions as a result of their capacity to examine and organize the data that they have received. As a result of taking this strategy, you will arrive to some form of conclusion or conclusion by the end of the process.

The concept of machine learning is taken a step further with the development of deep learning. The purpose of deep learning is to continuously learn from the real world while also modifying the learning model so that it can take in new information and come up with new insights. The field of deep learning frequently makes use of neural networks. The application of neural networks is humanity's best hope for successfully modeling the structure and operation of the brain. Establishing, reinforcing, or diminishing the strength of connections between nodes in a neural network takes place in a manner analogous to how repeated experiences cause connections between neurons in the human brain to become more robust. It is possible to fine-tune the output quality of a neural network by assigning a greater or lower value to each connection in the network.

THERE ARE THREE ASPECTS OF ARTIFICIAL INTELLIGENCE THAT EXPLAIN HOW MACHINES LEARN

There is a widespread misunderstanding that artificial intelligence (AI) refers to just one type of technology. However, this is not the case. There isn't a challenge that can't be conquered with the right application of artificial intelligence, which consists of a range of subsystems that can each be utilized in their own unique way. The standard artificial intelligence system is made up of sensing components, processing components, and learning components, all of which are connected to one another (see figure 2).

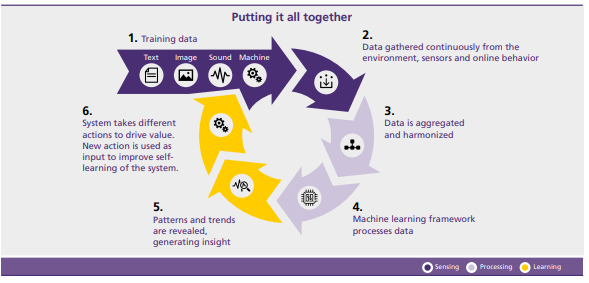


Figure 2: The complete cycle of AI learning.

SENSING IS THE KEY TO THE POWER OF ARTIFICIAL INTELLIGENCE.

The ability of an artificial intelligence to "detect" the real world is dependent on its capacity to process input. Because information in the real world arrives in a wide variety of formats, Artificial Intelligence (AI) systems need to be able to interpret data in a number of different ways. This comprises not just written words, photographs, and movies, but also sound and environmental elements such as temperature, wind speed, and relative humidity.

Processing information based on text is a more advanced form of AI sensing. In spite of the fact that artificial intelligence systems have for a long time handled structured data from sources such as databases, spreadsheets, and the internet, recent breakthroughs in deep learning have boosted AI's capability to manage and interpret unstructured data. On the internet and on social media, there are many different kinds of communication that are not structured, and this is an important quality that AI may exploit to improve its understanding of the world.

Using microphones, artificial intelligence (AI) systems can already record and analyze a significant number of the speech conversations that take place among us. AI systems are able to consider the environment in which spoken words were recorded, and if they have access to large enough datasets that also contain phrases that are similar or connected to one another, they can turn information that was previously useless into important knowledge.

Because of recent improvements in speech-to-text technologies, it is now feasible to control AI with one's voice. Voice assistants powered by AI can understand significantly more than humans can at this point. The word error rate is the single most critical metric that may be used when attempting to evaluate the performance of a speech-to-text system in terms of translating and understanding words. A typical discussion between two people has a 6 percent miscommunication rate, which means that 6 percent of the words being exchanged are not being understood properly. Machine data from the Internet of Things (IoT) is already being made available to AI-based systems, frequently for the first time. This enables the most advanced AI-driven voice assistants to be developed. Even with today's most modern data analytics tools, the Internet of Things can make it difficult to make sense of massive heterogeneous datasets and learn from the information contained within them. These datasets are collected from enormous fleets of heterogeneous devices.

STRUCTURES AND INSTRUCTIONAL APPROACHES FOR INFORMATION PROCESSING AND LEARNING

An artificial intelligence system does an analysis of the data it has gathered from sensing by utilizing a learning framework. It then makes use of this information to produce new insights. There are a lot of parallels between human intelligence and artificial intelligence, notably the way in which both types of intelligence learn new things. Adults are better able to seek out their own inputs and learn from the world around them as they grow older. Whereas children learn best from their parents and teachers in highly organized situations with a lot of reinforcement, adults are better able to learn from the world around them. In the same manner, artificial intelligence systems utilize supervised learning, unsupervised learning, and reinforcement learning in order to take in data about the environment around them and interpret that data.

The technique through which humans instruct an AI-enabled system is referred to as "supervised learning," which is also the name of the phrase. If a medical professional annotates x-ray images with his or her knowledge and then feeds them into an AI system, the AI system will be able to reap the benefits of supervised learning. Another application of supervised learning is when an artificial intelligence system searches through x-ray images and sends them to a human physician for examination and approval in order to assist in the development of the AI system's capacity for learning.

An AI-enabled system is able to uncover clusters or dimensions in the data all by itself in the case of unsupervised learning; this type of learning does not require any additional guidance from human data analysts or computer scientists. This approach has the potential to generate a diverse set of original and unforeseen results on the basis of the information to which the system is subjected. In 2014, YouTube was able to identify cat faces in uploaded videos simply by "watching" 10 million of them without being given any direction regarding the desired end result. This enabled the platform to accomplish this feat.

Reinforcement learning allows an AI system to learn both the "rules of the game" and how to process inputs in order to improve its performance. On the basis of data obtained by the AI system's interactions with the environment, as opposed to data directly gathered from human interaction. When an infant is unable to walk on their own, they first learn how to walk by watching others walk. A similar illustration of reinforcement learning can be seen here. They initially struggle mightily when attempting to walk independently, but ultimately, they get the hang of it and are able to do so without help. AlphaGo was able to learn how to play and beat any opponent by ingesting a large number of finished and ongoing Go games. This allowed AlphaGo to simultaneously understand how the game works and how to play the game.

Today's machine learning frameworks come in a wide range of flavors, but they all share a commonality in that their core capabilities are underpinned by neural networks. Data scientists and software engineers have access to a variety of frameworks that can be utilized in the process of developing AI solutions; however, each framework possesses an own set of advantages and disadvantages.

WALDO, which stands for "Wireless Artificial Intelligence Location Detection," is a system for the wireless detection of artificial intelligence in locations. Where is the value in that?

When it comes to detecting Wireless Location, there are a lot of reasons to believe that right now is the best time to make use of AI. This is as a result of the fact that it is now possible to integrate mm Wave communications and machine learning that is based on sensing. Getting your hands-on cutting-edge technology has never been more accessible or more affordable than it is right now.

SCOPE AND OBJECTIVES

The purpose is to use Python as the programming language to execute the code or Dataset provided and obtain a result that fits the ground truth. As a result, the source code for each milestone would be examined for efficacy before being made available for review. Python was studied and put to use. A prepared machine learning dataset from the ITU IEEE 802.11 challenge will be used as an input to the project to:

⦁ Check for signal fluctuation in a localized context by detecting motion using a provided dataset.

⦁ To check for signal fluctuation in a localized context, detect motion using a specified dataset.

⦁ Get the result of the ML in a 3D matrix (Ns, Na, Nc)

⦁ Compare the code against other types of coding to see how effective it is.

ACHIEVEMENTS

The technical and theoretical understanding of the requirement and understanding is achieved. Thus, finding several targets moving throughout the room and which sector. Across the Dataset, the number of targets, velocity of each target, and trajectory are to be randomized. The file also includes noisy IEEE 802.11ay channel estimate fields. The Dataset is appropriate for developing and testing machine learning or deep learning methods.

On the other hand, other difficulties were discovered when working on the supplied Dataset. For instance, the Dataset was too large to download. Moreover, the remote file link was not working and could not be reached.

OVERVIEW OF DISSERTATION

Following this introduction, the other portions of the report are organized in the following manner: In Section II, which highlights necessary enabling technologies for some of the related works done by other experts with emphasis placed on the concepts of localization, counting and sensing. In the following section (III), which highlights the methodology used in the process of model development and training is discussed in detail. In the following section (IV), which highlights the presentation and discussion of our results is achieved in two stages; training and testing phases. Section (V) ends with a brief review of our forecasts for the development of 6G localization and sensing in the future, as well as several questions that do not have definitive answers.

BACKGROUND THEORY AND LITERATURE REVIEW

Over the past few years, a significant number of studies have been carried out on the topic of indoor localization; below, we have included a summary of some of the more significant of these investigations. Mohammedi and Al-Fuqaha came up with an idea for a method of learning that is semi-supervised and is based on deep reinforcement (2018). The purpose of their model was to enhance the accuracy and performance of the learning agent. This was accomplished by making their model user-friendly for the use of smart city technology due to the fact that it uses both labeled and unlabeled data in its analysis. They apply their concept to the problem of overcoming the difficulty of interior localization in smart buildings by basing it on the strength of BLE signals. The implementation of indoor localization as a fundamental component of the services provided by smart cities will be required in those cities where a significant portion of the population spends the majority of their time inside. The model learns the optimal action policies that lead to an accurate estimation of target locations with a 23 percent improvement in distance and at least a 67 percent increase in incentives received. When compared to the supervised DRL model, this model is able to learn these optimal action policies. As an approach for localization, the use of relative signal strength indication (RSSI) in conjunction with K-nearest neighbor (KNN) profiling has been suggested. It has been demonstrated that it is possible to acquire precise estimations while incurring only a negligible amount of expense by employing this method (Haque & Assi, 2013).

The results that Wang et al. (2013) obtained were obtained through the usage of BLE RSS reading. They took up one seat in each of the classroom's four corners, which measured 6 feet by 8 feet. We used these three distinct methods in order to evaluate the experiment's precision. The strategy known as Least Square Estimation (LSE) is superior to the other two methods in terms of precision. Over the course of the past few years, a variety of novel strategies for positioning have been created. Through the application of machine learning strategies developed specifically for this industry and the examination of Received Signal Strength (RSS) fingerprints compiled from a significant number of base stations, new information was extracted from cellular base stations. To ensure that these findings are reliable and accurate, they were compiled over the course of an entire month of research. Support Vector Machines, either one-on-one or one-on-all, can be used to classify rooms at the room level with a precision of one hundred percent. In addition, when a semi-supervised learning technique was used... there were remarkable results. These remarkable results, which through the use of this technique were used a few sections of the training data that are required to have a room label, are also presented while indoor RSS localization utilizing WIFI is used for RSS (Oussar, Ahriz, Denby, & Dreyfus, 2011).

A Bluetooth radio that is powered by a battery and emits radio waves is known as a battery-operated beacon (Inoue, Sashima, & Kurumatani, 2009). There is some duplication in the tasks that are performed by lighthouses and beacons. The signals are continuously broadcasted in a manner that is analogous to that of Bluetooth-Low-Energy (BLE), which transmits signals that carry a minuscule bit of data routinely over a short distance while consuming a far lower amount of power than standard Bluetooth does. iBeacon makes use of a protocol or method for delivering (simply emitting) signals in order to make it possible for mobile devices, such as smartphones, to scan and display the contents of beacons that are within defined ranges (Inoue, Sashima, & Kurumatani, 2009). The functioning of the iBeacon is demonstrated in Figure 1. The RSSI value at each one-meter distance constitutes an additional byte of data that is broadcast by the device. This number is used to determine the power of an iBeacon. The received signal's strength can be quantified using the RSSI indicator. The unit of measurement for this is the decibel mill watt. demonstrates the strength of the signal sent out by the beacon as well as the close range at which it was evaluated (Inoue, Sashima, & Kurumatani, 2009; Jianyong, Haiyong, Zili, & Zhaohui, 2014).

SYSTEM FOR INDOOR POSITIONING

Modern technology known as an indoor positioning system (IPS) has become a hot topic in industrial, scientific and academic circles because of its ability to locate robots, people, and other things within a specific area of an interior. Radio waves, lighting, and auditory signals are all used in the process of locating items via communications and sensor technology (Jianyong, Haiyong, Zili, & Zhaohui, 2014). Each of the four basic IPS technology categories — proximity, fingerprinting, trilation, and motion — is used alone or in combination to improve accuracy. IPS technologies fall under these four broad headings. While proximity does not reveal an exact location, it does show how close a receiver is to the object being tracked. To determine a mobile device's location, RSSI is used to estimate the distance between mobile devices and beacons in order to determine the location of the mobile device. Bluetooth, IR, and RFID are all examples of systems that make use of proximity (Brena, et al., 2017).

POST DETERMINATION THROUGH A NEURAL NETWORK ALGORITHM OF K-NEAREST NEIGHBOR

A nonparametric technique known as K-nearest neighbors has been utilized for classification and regression in the field of pattern recognition. To train classification and regression models, the input is composed of the k nearest training samples in feature space. Classification or regression using the K-nearest neighbor technique yields different results (Ponraj & Kathiravan, 2019). K-NN classification results in a class that is a member of a group with the same features. By adopting a technique known as majority voting, K-NN is able to classify its K-NNs, with the most points going to the most popular classes. There are no special considerations in class assignment when k equals one. K-NN regression provides the property value for a given place in space as the output. The average of the values of the k closest neighbors is this value (Ponraj & Kathiravan, 2019; Amiri, et al., 2016).

ARTIFICIAL INTELLIGENCE DERIVED FROM CELLULAR NETWORKS

Cellular networks will have more access and service provisioning options to pick from in the 5G future, which will pave the way for the utilization of preparation information. Despite all of this advancement, 5G mobile networks have not yet reached the point where they can satisfy the expectations of customers in a practical sense. When it comes to configuring a standard 4G node, the number of adjustable parameters has increased from 500 in a 2G node to 1500 in a 3G node. This is an increase from the previous number of parameters, which was 500 in a 2G node. If the current trend continues, a typical 5G node might contain as many as 2,000 characteristics by the year 2020. This is assuming that the trend will continue. In light of this fact, the development of self-organizing capabilities in the 5G era will necessitate an increase in intelligence (e.g., self-configuration, self-optimization, and self-healing). To start, the types of service that are defined for the age of 5G (eMBB, URLLC, and mMTC) are set in stone. Both previously established patterns of service delivery and newly conceived kinds of services are continuously evolving in tandem with one another. In a 5G mobile network, there are no functionalities that would allow for the automatic detection, provisioning, or establishment of a new service type. Consequently, such a service cannot be added. SDN-based network design is dependent on the inability of 5G to adapt and be robust in the face of ever-increasing heterogeneous and complex cellular networks. If cellular networks are to self-organize parameters that grow significantly, automatically build network slices for new services, and gain enough flexibility for network maintenance, they need the ability to observe changes in their environment, learn uncertainties, plan responses, and properly configure their networks. Inadvertently, this leads to the discovery of new varieties, classifications, and future issues, all of which can be resolved by interacting with one's surrounding environment. It is therefore possible to use the concept of cognitive radio [10] and use AI to interact with the environment, which paves the way for a completely new intelligent 5G era to be fully accelerated. [Cognitive radio] refers to a type of radio technology that can learn from its surroundings. [AI] uses data collected from sensors

The study of artificial intelligence has given rise to the development of multidisciplinary approaches, such as machine learning, optimization theory, game theory, control theory, and metaheuristics [11]. One of the most significant facets of AI is the field of machine learning. Depending on the characteristics of the learning objects and the input signals to a learning system, machine learning is frequently subdivided into the following three primary categories:

Educating oneself while being watched: A learning agent will be given both inputs and outputs, and it will work to discover a general rule that can convert inputs into outputs based on the information it receives. Supervised learning has seen widespread adoption in the field of cellular networking as a means of addressing channel estimation issues. If, for instance, there is a wireless channel h, the receiver will attempt to estimate h by combining data from the broadcast preamble s with the received signal y = hs + n0. This will be done in the event that there is a wireless channel h. In this scenario, which is common in supervised learning, use probabilistic models to characterize the transition probability P(y|s) to y and Bayes procedures to obtain the results. In addition, the well-known Kalman filtering method and the particle filtering method also play an important part in the optimization of cellular networks.

Unsupervised Learning: When it comes to unsupervised learning, the input information does not include any priori labels. This is in contrast to supervised learning, which was previously discussed. An intelligent agent that learns must rely on its own capabilities in order to unearth the concealed structure or pattern contained in its data. The goal of unsupervised learning is often to identify patterns in the input data that aren't immediately obvious, and then to construct an appropriate representation for those patterns. Unsupervised learning plays a significant role in the deep learning methodology, which is used to estimate the parameters of neural networks' hidden layers. More than any other form of artificial intelligence, cellular networks rely heavily on unsupervised learning. For instance, PCA and SVD algorithms have been used to modify the receiving matrix of massive MIMO in order to reduce the amount of complexity that is associated with computation. In addition to using the expectation-maximization technique, 5G NoMA receivers also use the message-passing algorithm to help lower the bit error rate. The K-means algorithm is one example of a classifier that may be used to search for and identify anomalies in a network.

Learning through Experience: The fields of control theory and behaviorist psychology served as inspiration for reinforcement learning, which enabled it to accomplish its goal through the process of interacting with a dynamic environment. On the other hand, the agent is unaware of whether or not it is moving any closer to the goal that it has set for itself. In a Markov decision process, one alternate course of action for the agent would be to take steps that would maximize the total amount of cumulative rewards (MDP). As a consequence of this, reinforcement learning has an exceptionally high capacity for pattern identification. Researchers in the field of cognitive radio use methods of reinforcement learning (such as Q-learning and the actor-critic method [12, 13]) to determine whether or not secondary transmission in one primary licensed spectrum is appropriate in terms of causing the least amount of interference to the primary spectrum. This decision is made in order to maximize the efficiency of the primary spectrum. [12,13]

Since it is anticipated that the 5G new radio (NR) would be widely released by the year 2020, the technology has already reached its initial maturity level, and the first networks have been installed. In point of fact, there is already an urgent requirement to start thinking about the next generation of wireless communication networks, which has been dubbed the sixth generation (6G) for its abbreviated form. In the context of potential future 6G wireless communication networks, this study focuses on the most significant aspects of the localization and sensing operations. Wireless networks are often acknowledged for their communication capabilities; however, the inherent benefits they offer in terms of localization and sensing are frequently disregarded. Because of its enormous bandwidth, extremely high carrier frequency, and gigantic antenna array, 5G New Radio (NR) is ideally suited to serve as a platform for precise localization and sensing systems. In addition, 6G systems will continue to develop in the direction of even higher frequencies, such as millimeter wave (mm Wave) and THz1 ranges, as well as much broader bandwidths. This development is expected to take place in the coming years. In point of fact, the THz frequency range provides a multitude of benefits, such as the capability to carry out high-resolution imaging and frequency spectroscopy in addition to accurate localization. Before highlighting the potential of mm Wave and THz frequencies to allow localization and sensing solutions for 6G, the authors [1] present an introduction to wireless communications and some of the uses that are anticipated to be supported by 6G networks operating at frequencies higher than 100 GHz. In the same vein, the potential possibilities of 6G networks in the cellular sector are discussed in [2].

The 5G New Radio (NR) standard provides support for two distinct frequency bands: sub-6 GHz and mm Wave. These frequency bands operate in the frequency ranges FR1 (410-7125 MHz) and FR2 (24250-52680 MHz), respectively [3]. In addition, the NR standards account for both Standalone (SA) and Non-Standalone (NSA) modes of operation. You have the option of using the 4G LTE network and adding the 5G carrier as a secondary layer, but if you'd rather, you can also use the 4G LTE network and add the 5G carrier at the same time. Either way, the choice is yours. Enhancements to beamforming, user equipment power saving, dynamic spectrum sharing, dual connectivity, and carrier aggregation are just some of the new features that are included in Release 16 of the 5G New Radio standard. In addition, the 5G New Radio (NR) has advanced features for major vertical markets such as ultra-reliable low latency communication (uRLLC), support for intelligent transportation systems and vehicle-to-anything communications, and positioning capabilities in relation to the overall infrastructure and new deployment scenarios. These features include the industrial internet of things and ultra-reliable low latency communication (uRLLC). Advanced positioning architecture in NR systems typically consists of the radio access network (RAN), the core networks, the relevant positioning server, a location service client, and a centralized location service provider. Additionally, the advanced positioning architecture may also include the target user. It is possible to transmit positioning data between the user device that is being targeted, the network elements, and the positioning server through the use of communication in the control plane. The LTE positioning protocol (LPP) extension specifies a signaling exchange that must take place between a target user equipment (UE), a location server, and a location management function (LMF) [4]. (LMF). According to NRPPa, it is equally important to have protocols in place that allow the transfer of positioning-related information between the next generation of RAN nodes and the LMFs that accompany them. [5] In accordance with the 3GPP specifications, LPP messages are transferred between core networks and the UEs that are the focus of the transfer using the NR-Uu interface [6, 7]. For instance, the LMF will send positioning requests to the serving base stations, which could be either gNB or ng-eNB. The serving base stations will then provide location information (based on the measurements of the reference signals) to the target UE, in addition to performing uplink measurements. It is important to take note of this.

The 5G New Radio (NR) access interfaces present new use cases for location data, and the majority of these new use cases are self-explanatory. In addition, augmented reality and health care, as well as haptic technology, are examples of emerging uses for the internet of things in a number of different industry areas. One illustration of this would be the tracking of assets. After a Study Item that was intended to investigate this subject and was finished in 2019, a Work Item is currently being developed by the 3GPP standards organization to provide a description of the positioning support for Release 16 and following versions. First and foremost, the next generation of high-precision positioning services needs to be able to achieve an accuracy level of less than one meter throughout more than 95% of the network area [7]. (including indoor, outdoor and urban deployments). 5G New Radio (NR) establishes several different radio access ways for the purpose of locating solutions. These methods include time difference of arrival uplink/downlink (TDOA), multi-cell round trip time (RTT), and uplink angle of arrival/departure (AOA). Numerous physical layer measurements are required for the NR positioning methods that are now in use. The reference signal timing difference is something that already exists in LTE networks and is something that may be used in conjunction with beam-based location reference signals. This is a baseline configuration for 5G New Radio (NR). Another possibility is to make use of the time disparities between the UE receiver and the UE transmitter. These time differences are defined for serving cells and neighboring cells in NR, and they can be applied to the calculation of the overall multicell round trip time. When RAN1 setups are being discussed, the relative time of arrival for each beam is also something that is taken into consideration. In order to support high-accuracy positioning in Rel-16 and future releases, it is necessary to improve on the existing reference signals, such as the channel state information reference signal (CSI-RS) for beam management, the CSI-RS for time-frequency tracking, the CSI-RS for mobility measurements, the phase tracking reference signal (PTRS), and the demodulation reference signal (DMRS). Recent discussions in the technical specification group have focused on the challenges that are still present for positioning that is dependent on uplinks and downlinks. Standardization bodies have reached an agreement to implement new measurements in the Uplink direction. These new measurements will support UL relative arrival time, azimuth angle of arrival (AoA), zenith angle of arrival (ZoA), and UL reference signal received power (RSRP) measurements. Additionally, new measurement reports will include carrier phase estimation at both serving and neighboring gNBs. In the commercial use cases (including Industrial IoT scenarios), which are currently being studied and worked on, a lot of attention is also being paid to how to support high accuracy and low latency transactions (on both the user and control planes), while also reducing the amount of complexity, scalability, signaling overhead, and power consumption. This is being done on both the user plane and the control plane.

Location and sensing information can be used by mobile communication systems for a variety of purposes, including but not limited to the following: the localization of emergency calls through Enhanced 911 (E911); the detection of intruders through walls; the provision of personal navigation and radar; the tracking of robots and drones; and the facilitation of social networking. The design, operation, and optimization of communications networks can all benefit from the utilization of location-based information. Both Taranto et al. and Koivisto et al., for example, presented an overview of location-aware communications for 5G networks across multiple protocol stack layers. After that, they highlighted positive trends in addition to compromises and issues. In addition, the possibility of enhanced synchronization across networks is discussed in [14]. In [15], the authors present an overview of localization strategies for applications involving 5G NR and the Internet of Things. They begin by going through the most essential enabling technologies and features of 5G networks, and then they move on to identifying the most important practical implementation issues and prospective development paths for localization-based services. According to Lohan et al. in [16], Industrial Internet of Things (IIoT) installations can be improved by leveraging position side-information. [Citation needed] The central question of this essay is, "How will these concepts, ideas, and services evolve in the future when 6G technology is fully implemented?"

It is important to note that the development cycle for 5G New Radio (NR) has reached a mature level, and researchers are gradually shifting their attention to the potential technologies and systems for 6G [2], [17]–[23]. This is important to keep in mind for all intents and purposes. We believe that our contribution is the first to focus on the 6G convergent communications, localization, and sensing systems by identifying the most promising enabling technologies, discussing desired features, new applications, and opportunistic opportunities. This was accomplished by identifying the most promising technologies, discussing desired features, new applications, and opportunistic opportunities.

Summary

Unlike the related works discussed above, "The Wireless Artificial Intelligence Location DetectiOn challenge tackles one most promising applications of current 5G and future 6G wireless systems" [7]. Beyond 5G (B5G) systems are built to meet ever-stricter requirements, such as combining communications, sensing, location, and computation services. 6G will be an intelligent wireless system that will allow high-accuracy localization, high-resolution sensing services, and ubiquitous communication. Deep Neural Networks are a new generation of Artificial Neural Networks (ANNs) that are used in this technology as opposed to the use of K Nearest Neighbors algorithms which were the most used algorithms in doing the implementations as explained in various works above.

METHODOLOGY

DATASETS DESCRIPTION

REFERENCES

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