8-2023

Generalizable Deep-Learning-Based Wireless Indoor Localization

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A Thesis
Presented to
the Graduate School of
Clemson University

In Partial Fulfillment
of the Requirements for the Degree
Master's
Computer Engineering

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by
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August 2023

Accepted by:
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Abstract

The growing interest in indoor localization has been driven by its wide range of applications in areas such as smart homes, industrial automation, and healthcare. With the increasing reliance on wireless devices for location-based services, accurate estimation of device positions within indoor environments has become crucial. Deep learning approaches have shown promise in leveraging wireless parameters like Channel State Information (CSI) and Received Signal Strength Indicator (RSSI) to achieve precise localization. However, despite their success in achieving high accuracy, these deep learning models suffer from limited generalizability, making them unsuitable for deployment in new or dynamic environments without retraining. To address the generalizability challenge faced by conventionally trained deep learning localization models, we propose the use of meta-learning-based approaches. By leveraging meta-learning, we aim to improve the models' ability to adapt to new environments without extensive retraining. Additionally, since meta-learning algorithms typically require diverse datasets from various scenarios, which can be difficult to collect specifically for localization tasks, we introduce a novel meta-learning algorithm called TB-MAML (Task Biased Model Agnostic Meta Learning). This algorithm is specifically designed to enhance generalization when dealing with limited datasets. Finally, we conduct an evaluation to compare the performance of TB-MAML-based localization with conventionally trained localization models and other meta-learning algorithms in the context of indoor localization.

Acknowledgments

I wish to extend my heartfelt appreciation to my advisor, Dr. Fatemeh Afghah, for her assistance, patience, mentorship, and backing during the course of my studies. Her vast knowledge and encouragement were instrumental in enabling me to successfully conduct this research and compose this thesis.

Additionally, I would like to express my gratitude to Dr. Linke Guo, and Dr. Kuang-Ching Wang for their role as a member of my thesis committee and for offering invaluable feedback and recommendations. Their valuable insights and guidance played a significant part in shaping my research and facilitating the writing of this thesis.

I would like to extend my appreciation to my fellow colleagues at Clemson University for their encouragement and teamwork throughout my research endeavors. I am especially grateful to Chun-Chih Lin for his valuable assistance with collecting the dataset that was used to evaluated the proposed method in this thesis. His contributions have been instrumental in the successful completion of my research.

Finally, I wish to express my gratitude to my family and my loved ones for their unwavering love and encouragement throughout this journey. Their support has been indispensable, and I recognize that this endeavor, just as the previous ones, would not have been achievable without their presence in my life.

Parts of the material used in this thesis are based upon work supported by the Air Force Office of Scientific Research under award number FA9550-20-1-0090 and the National Science Foundation under Grant Numbers CNS-2204445 and CNS-2232048.

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Chapter 1

Introduction

Indoor localization has experienced a surge in importance in recent years, primarily due to its wide range of applications and their growing significance across various domains. Industries such as logistics, healthcare, retail, and public safety heavily rely on accurate and real-time location information within indoor spaces. The ability to precisely track assets, manage inventory, optimize operations, and ensure safety in complex indoor environments has become paramount. Moreover, indoor localization plays a crucial role in improving customer experiences, enhancing personalized marketing, enabling efficient navigation, and facilitating resource management. The increasing adoption of smartphones, IoT devices, and advanced wireless networks has further fueled the demand for robust and reliable indoor localization solutions. This heightened importance is reflected in the rising research efforts, commercial deployments, and standardization initiatives aimed at advancing indoor localization technology and unlocking its full potential in addressing the unique challenges and requirements of indoor environments.

Contrary to outdoor localization, where line-of-sight (LOS) is present in most instances, there are a lot of challenges in indoor localization, such as the presence of physical barriers, multipath effect, and the complexity of indoor environments. Outdoor localization methods, such as GPS, are not suitable for indoor localization despite their accuracy in outdoor settings due to fundamental differences in the indoor environment. GPS relies on signals from satellites, which are attenuated or blocked by buildings, resulting in degraded or no reception indoors. Additionally, GPS requires a clear line of sight to multiple satellites for accurate positioning, which is hindered by walls and obstructions indoors. The granularity and precision required for indoor localization, such as distinguishing between different rooms or objects, exceed the capabilities of GPS, which typically provides accuracy in the range of several meters. The limited penetration of GPS signals through building materials and the scarcity of visible satellites within indoor spaces further limit its effectiveness. Due to all these challenges, researchers have been focusing on developing localization methods tailored for indoor localization instead.

1.1 Localization Techniques

Indoor localization has witnessed the application of numerous techniques to estimate the location of objects or individuals within enclosed spaces. Various approaches, including fingerprinting, triangulation, dead reckoning, and proximity detection, have been employed to achieve this goal. Each technique offers advantages and may cater to specific indoor environments or use cases, leading to a diverse range of solutions for indoor localization challenges. In this section we discuss some of the commonly used techniques for indoor localization. Taxonomy of the discussed techniques are depicted in Figure 1.1. Moreover, a summary of comparisons between the techniques are presented in table 1.1.

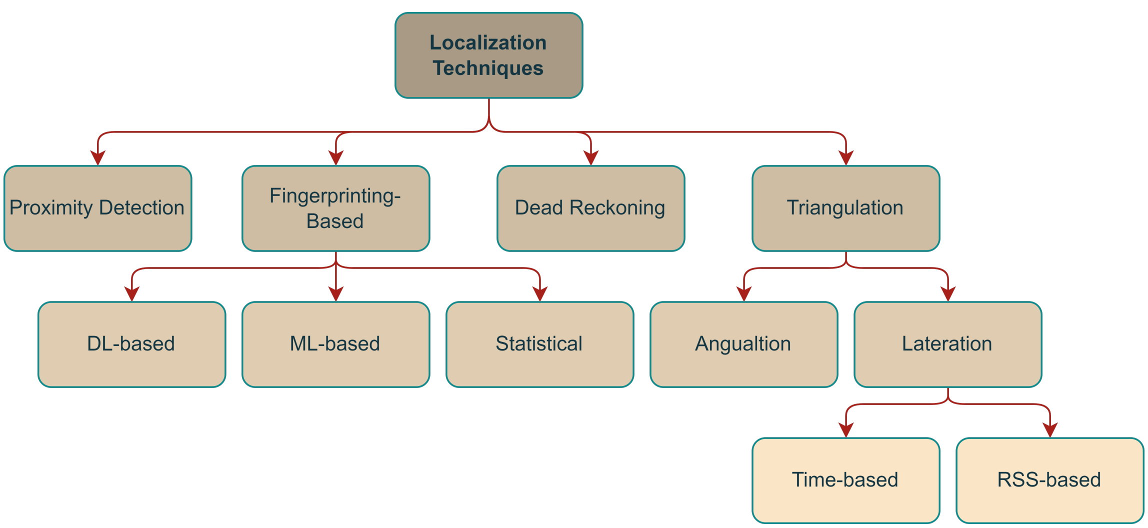


Figure 1.1: Taxonomy of indoor localization techniques

Table 1.1: Comparison of Indoor Localzaition Techniques.

Technique	Accuracy	Advantages	Disadvantages
Fingerprinting	High	Less affected by multipath effects Integration with data-driven methods	Callibration and data collection
Proximity Detection	Low	Low cost and simple	Approximation of the location
Time-based Lateration	Medium-High	High accuracy with LoS	Heavily affected by multipath effects Synchronization needed
RSS-based Lateration	Medium-High	High accuracy with LoS	Affected by multipath effects
Angulation	High	High accuracy with LoS	Heavily affected by multipath effects Antenna array needed
Dead Reckoning	Low-Medium	Self-localizing method	Susceptible to cumulative error Extra sensors needed

1.1.1 Triangulation

Triangulation techniques are methods that leverage the geometric properties of triangles to determine the location of the target, by forming triangles between known points. Triangultion has two main approaches: lateration and angulation. Lateration, a distance-based technique, employs measurements like Time of Arrival (TOA) and Received Signal Strength (RSS) to estimate the object's position. On the other hand, angulation, a direction-based technique, utilizes Angle of Arrival (AOA) to determine the target's location relative to multiple reference points.

1.1.1.1 Lateration

In lateration, location of an object is measured by its distance from multiple APs. Parameters such as RSS, ToA are commonly used as measurements of the distance between an object and an access point. Each distance equation will specify a circle in the 2D space (and a sphere in the 3D space). In 2D, two equations yield two potential solutions, but for a definitive result, three equations are necessary. The intersection of these equations, depicted in Figure 1.2, identifies the object's location. In 3D scenarios at least four APs are required to achieve a unique solution [123].

Furthermore, differential measurements such as Time Difference of Arrival (TDoA) or Differential Received Signal Strength (DRSS) can also be utilized for lateration. Differential measurements can help mitigate the impact of environmental changes. In cases where the transmitted power or

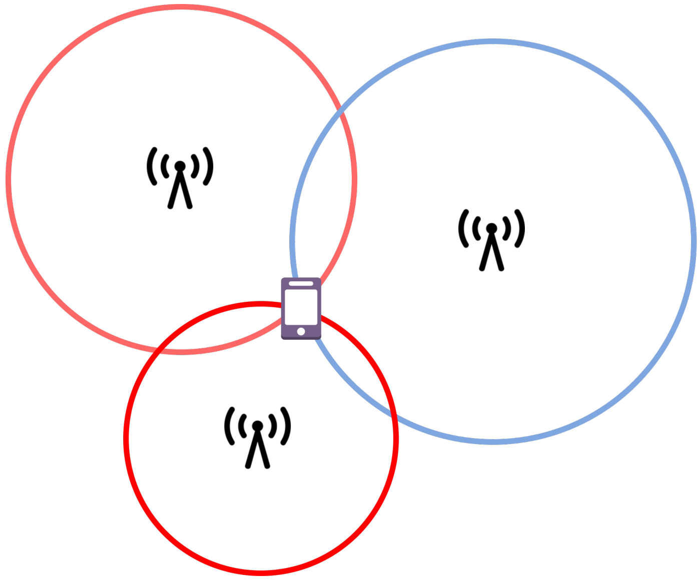


Figure 1.2: Lateration localization in 2D space.

the transmission time are unknown, differential measurements are beneficial [38]. Moreover, in the case of time-based lateration, using differential measurements such as TDoA will eliminate the need for synchronization between the target object and the other APs [7]. When n APs are present in a lateration localization system, a total of (n(n1)/2) differential equations are formulated. Out of all the formulated equations only (n-1) are base equations and the rest are redundant linear combinations of the base equations. Each base equation will specify a hyperbola in a 2D space. To have a unique solution, 3 base equations are required in a 2D space, meaning that at least 4 APs are needed when differential measurements are used compared to the three required APs when distance measurements are utilized.

1.1.1.2 Angulation

Angulation is a method employed to determine the location of an object by calculating angles relative to multiple reference points, utilizing measurements like Angle of Arrival (AoA). This process involves using directional antennas or antenna arrays, which can lead to higher implementation costs. In 2D spaces, localizing an object requires two angle measurements and a single distance measurement, as depicted in Figure 1.3. The distance measurement could be represented as the distance between the APs. In 3D spaces, the process requires two angle measurements, a single azimuth measurement, and a distance measurement [22]. Although two APs are required for angulation, in many cases three or more APs are utilized to enhance accuracy.

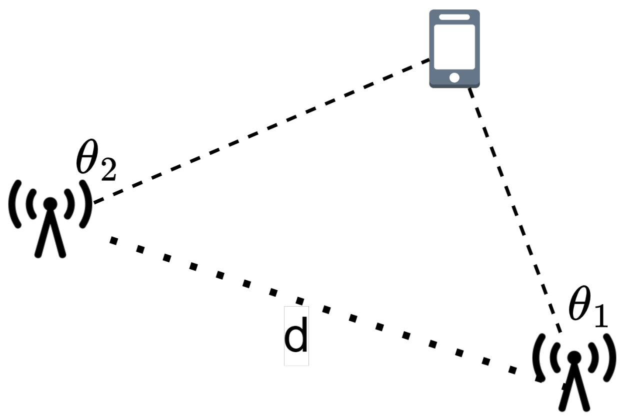


Figure 1.3: Angulation localization in 2D space.

1.1.2 Fingerprinting

Localization based on fingerprinting is a widely used technique for determining the location of an object within an indoor environment. In the fingerprinting technique, various features of the environment are collected as fingerprints from different locations within the target area, forming a database. The core concept involves matching the measurements from a target object, with the pre-built database of fingerprints to compute the target object's location [19]. The fingerprinting process consists of two phases: the offline/calibration/training phase and the online phase. In the offline phase, the fingerprint database is established within the area of interest at a certain level of granularity, where finer granularity often leads to improved accuracy but requires more effort and time for fingerprint collection. The built fingerprint dataset acts as a radio map which serves as a reference for the localization process. In the online phase, the object's location is determined by matching the collected fingerprint with the fingerprints in the database using deterministic or probabilistic algorithms.

Fingerprinting does not necessitate specialized hardware (as needed in the Dead Reckoning technique) or time synchronization (as needed in time-based lateration). Moreover, the data-oriented nature of the fingerprinting technique makes it a suitable approach for applying Machine Learning and Deep Learning methods. However, fingerprinting approach does have drawbacks, including the laborious and time-consuming offline process, challenges in adding signal stations for building the fingerprint dataset, and sensitivity to environmental changes like object movement. To maintain positioning accuracy in time, periodic recalibration of the fingerprint dataset or retraining is needed.

1.1.3 Proximity Detection

Proximity-based indoor localization is a simple technique for determining the approximate location of objects within enclosed spaces. Wireless devices receive signals that are above a certain threshold in terms of power, below which received power signals are considered noise, indicating the device is out of the AP coverage area. Above this threshold, the mobile and AP are connected, and the device is within the coverage area [50]. By considering the intersection between AP coverage areas, localization accuracy can be improved. Although proximity detection techniques are relatively simple to implement, they are limited in coverage area, and the achieved accuracies are lower than other techniques. Hence, they better be implemented alongside other techniques to narrow down the possible locations.

1.1.4 Dead Reckoning

Dead reckoning is a technique used in localization to estimate the current position of a mobile entity without relying on external positioning systems. Instead, it uses internal measurements of velocity and direction using sensors such as accelerometers, gyroscopes, and magnetometers to track the entity's movements from a known starting point. By continuously integrating these measurements over time, dead reckoning provides real-time updates on the entity's position. However, a drawback of dead reckoning is its cumulative inaccuracy, where the deviation in the estimated position increases over time. This happens because each new position is solely determined based on previous positions, leading to a growing error in the final position fix. While dead reckoning is a valuable method for short-term, it may encounter challenges in dynamic and unpredictable environments. To this end, hybrid techniques involving dead reckoning are utilized [3, 30] to enhance the accuracy and correct the accumulative error of dead reckoning in future steps.

1.2 RF Technologies Used for Indoor Localization

Many RF technologies have been studied as a medium for indoor localization, radio frequency identification (RFID), ultra-wideband (UWB), Bluetooth, and Wi-Fi [36]. In this section some of the main RF technologies used for indoor localization and their capabilities in the context of localization are are discussed. A high-level comparison of RF technologies in the context of indoor localization is presented in table 1.2. While there are localization methods that rely on camera/vision technologies, These methods are not discussed here as they are beyond the scope of this thesis.

1.2.1 Wi-Fi

Out of the proposed technologies, Wi-Fi has emerged as the predominant technology for indoor localization due to several key factors. Wi-Fi infrastructure is already pervasive in indoor environments, making it readily available for localization without the need for additional infrastructure deployment. Furthermore, Wi-Fi offers reasonable accuracy for indoor positioning by leveraging signal strength measurements and various localization algorithms. Additionally, Wi-Fi is compatible with a wide range of devices, such as smartphones and laptops, which already have Wi-Fi capabilities, eliminating the need for additional hardware. The extensive research and development in Wi-Fi localization techniques, coupled with its cost-effectiveness, further contribute to its prevalence for localization purposes.

1.2.2 Bluetooth

Bluetooth (IEEE 802.15.1) is designated for low power short-range wireless communication in the 2.4GHz ISM band. Bluetooth is widely available on smartphones and portable devices, which makes it more suitable for localization applications. Localization accuracy using Bluetooth is generally reported to be lower than Wi-Fi. In [54], a comparison between localization accuracy of Wi-Fi and Bluetooth with RSSI-based trilateration reported localization accuracies of 48.6 cm and 84.4 cm for Wi-Fi and ZigBee respectively. The lower power consumption of Bluetooth and it's compatibility with many portable devices makes Bluetooth a viable choice for efficient low range indoor localization and proximity detection applications where detecting the precise is not the most important obejctive.

1.2.3 ZigBee

ZigBee is a low-power, wireless communication protocol designed for short-range and low-data-rate applications. It is based on the IEEE 802.15.4 standard and operates in the 2.4 GHz frequency band. Although ZigBee's low power consumption and its integration in wireless sensor networks (WSN) makes it and interesting choice for WSN localization applications, ZigBee is generally not considered a good choice as it is not readily available on a majority of the portable devices and the obtained localization accuracy is usually lower. In [54], the authors compared the localization accuracy of Wi-Fi and ZigBee with RSSI-based trilateration method and reported localization accuracies of 48.6 cm and 91.1cm for Wi-Fi and ZigBee respectively.

1.2.4 RFID

Out of the two types of RFID (passive RFID, and active RFID), passive RFID is not a suitable choice for localization due to its extremely short range (1-2m). Active RFID on the other hand has a reasonable range and can be used for low energy and efficient localization systems. Moreover, although it currently not readily available on many portable user devices, it can be easily embedded in the tracking objects. The biggest downside to using RFID for localization is the limited localization accuracy that it offers (hardly reaching sub-meter levels), which makes it unsuitable for applications requiring high localization accuracy levels.

1.2.5 UWB

Multiple characteristics of UWB has made it a very suitable fit for indoor localization applications. UWB use low energy level for short-range, high-bandwidth communications over a large portion of the radio spectrum. UWB has higher immunity against interference from other signals due to its unique signal type and radio spectrum. Additionally, UWB signals, especially the lower frequencies within its broad spectrum, can penetrate various materials easier, which makes it a more resilient choice for highly obstructed indoor environments. Furthermore, UWB is less susceptible to disruptions caused by multi-path effects as it uses extremely short pulses (¡1 ns). All these desirable characteristics lead to a high localization accuracy when UWB is used. However, the limited adoption of UWB in consumer products and portable devices and higher cost for hardware requirements has currently prevented wide usages of UWB for indoor localization.

Table 1.2: High-level comparison of wireless technologies in the context of indoor localization

Technolgoy	Indoor Coverage	Power Consumption	Advantages	Disadvantages
Wi-Fi (802.11n)	Good Coverage	Medium	Widely Available High Accuracy	Relatively Higher Power Consumption
UWB	Good Coverage	Low	High Accuracy More Immune to Interference More Immune to Multi-path effects	Higher Cost Hardware Requirements Newer Technology, Less Developed
Passive RFID	Extremely Short Coverage	Extremely Low	Extremely Low Power Consumption	Very Low Accuracy
Active RFID	Good Coverage	Very Low	Very Low Power Consumption	Low Accuracy
Bluetooth	Shorter Range	Low	Low Power Consumption Widely Available	Lower Accuracy
ZigBee	Shorter Range	Very Low	Very Low Power Consumption	Lower Accuracy Not Readily Available on Devices

1.3 Parameters Used for Indoor Localization

Many different parameters have been utilized for indoor localization such as Time of Arrival (ToA) [39], Time Difference of Arrival(TDoA) [6, 62, 75], Received Signal Strength Indicator (RSSI), and Channel State Information (CSI), In this section a couple of these parameteres are introduced and discussed in the context of localization. It should be noted that to overcome the downsides of these parameters, normalization and post processing of data are often used in practice, alongisde incorporation of multiple parameters as a hybrid heterogeneous input data in some cases of data-driven indoor localization methods.

1.3.1 Received Signal Strength Indicator (RSSI)

RSSI is the most commonly used parameter for indoor localization [11, 18, 74]. RSSI is a simple measurement of the strength of the received signal and very easy to obtain compared to the other parameters. To acquire RSSI, There is no need for specialized hardware to besides a wireless network interface card [20]. In theory RSSI decreases monotonically with distance in free space [52], so it can be used to detect distance of the target wireless device. But in practice, RSSI is volatile and unreliable as multi-path effects, obstacles, attenuation, and changes in indoor environments severely effect RSSI measurements, making establishment of a highly accurate localization model using RSSI a difficult task.

1.3.2 Channel State Information (CSI)

CSI provides information about the channel characteristics between a device and an access point. CSI can provide more detailed information about the wireless signal, including phase and amplitude in different sub-channel and between each transmitter-receiver antennae pairs [79]. These characteristics of CSI lead into better multipath information, stable measurements, and improved localization accuracy. It should be noted, that although CSI is more stable than RSSI, it is still volatile and susceptible to environmental changes. On the downside, CSI's complexity may also require more complex ways of data preprocessing than simpler measurements such as RSSI [46]. Furthermore, there are extra hardware requirements for collecting CSI data. Currently, numerous IEEE 802.11 NICs cards have the capability to offer channel measurements at the subcarrier level for Orthogonal Frequency Division Multiplexing (OFDM) systems.

1.3.3 Time of Arrival (ToA)

The Time of Arrival (ToA) or Time of Flight (ToF) method utilizes the time taken for a signal to travel from a transmitter to a receiver to calculate the distance between them. ToA can be applied to localization systems using both radio frequency (RF) and acoustic signals [49]. By multiplying the ToA value by the speed of light (c = 3 × 108 m/sec), the physical distance between the utilizes and receiver can be determined. ToA measurements require precise synchronization between transmitters and receivers, often involving the transmission of timestamps along with the signal. ToA accuracy may be reduced with a low sampling rate in time, as the signal might arrive between the sampled intervals. It's important to note that ToA-based localization systems will significantly deteriorate in non-line-of-sight (NLOS) conditions which are not rare in indoor environments. This is because signal reflections and multi-path effects will effect ToA measurements severely.

The concept of lateration is commonly utilized in ToA-based localization [56]. In order to solve the equations involved in ToA localization, measurements from a minimum of three Access Points (APs) must be utilized. When dealing with a three-dimensional scenario involving coordinates, at least four APs are required to obtain a single, unique solution. [49]

1.3.4 Time Difference of Arrival (TDoA)

Time Difference of Arrival (TDoA) is a measurement of difference in signal propagation times between a target device and multiple anchor devices. To determine the target's position using TDoA in a 2D space at least four anchor nodes are required (three TDoA measurements), and five anchor nodes (four TDoA measurements) in 3D space [27]. Each TDoA measurement specifies a hyperboloid in the space and the intersection of hyperboloids are used to pinpoint the target's position [14].

TDoA offers some advantages over Time of Arrival (ToA) in terms of synchronization. While ToA requires synchronization of all devices, the target device and the anchor devices, TDoA only requires synchronization of the anchor devices, reducing the synchronization error [13, 57].

However, TDoA-based localization does not solve the issue of ToA-based localization with multi-path effects, and TDoA-based systems are also significantly affected by NLOS signal propagation, leading to degraded performance [44].

1.3.5 Angle of Arrival (AoA)

Angle of Arrival (AoA) approaches in localization utilize antenna arrays at the receiver side to estimate the angle at which the transmitted signal arrives. This is achieved by calculating the time difference of arrival at individual elements of the antenna array [77]. The advantage of AoA is that it can estimate the location of a device with as few as two anchor nodes in a 2D environment or three monitors in a 3D environment [81]. However, AoA requires complex hardware and careful calibration, and its accuracy decreases as the distance between the transmitter and receiver increases. Even a slight error in the angle of arrival calculation can result in a significant error in the actual location estimation [32]. Additionally, obtaining accurate line-of-sight (LOS) AoA measurements in indoor environments is often challenging due to multipath effects.

However, a drawback of AoA is the need for antenna arrays, which adds complexity and cost to the system [55]. Time difference of arrival can also be employed in AoA, but it necessitates even more complex hardware and precise calibration. Moreover, AoA is highly sensitive to multipath and NLOS conditions, as well as the precision of the antenna array [70].

1.4 Traditional and Data-Driven Localization Methods

Traditional indoor localization methods, such as dead reckoning, proximity detection, triangulation, and fingerprinting using statistical methods, have been widely used for indoor localization. Proximity detection is not an accurate and reliable method and introduces a lot of localization error. Dead reckoning is susceptible to cumulative error and it is best used in conjunction with another technique. Triangulation methods leverage the principles of distance measurements and angle calculations to estimate positions. These methods offer benefits such as simplicity, scalability, and compatibility with minimal infrastructure. They require relatively low computational resources and can achieve reasonable accuracy in certain scenarios. Triangulation techniques can reach high accuracies in open spaces with LoS. However, as these methods heavily rely on accurate distance measurements or angle estimations, they are drastically effected by signal propagation issues, multipath effects, and environmental obstacles, challenges that we commonly face in indoor environments. Moreover, these methods are susceptible to errors introduced by measurement inaccuracies and noise, limiting their precision and robustness.

On the other hand, fingerprinting methods rely on pre-collected information from known reference points to create a database of signal fingerprints. These technique can achieve high accuracies and are more suitable for indoor localization as they are less affected by multipath effects comapred to triangulation methods. Moreover, fingerprinting methods offer flexibility in handling complex environments and can provide room-level or object-level localization. However, both fingerprinting-based techniques using traditional statistical methods, and fingerprinting-based techniques using DL and ML models, require labor-intensive data collection, periodic calibration, and may suffer from environmental changes, hindering real-time positioning accuracy. Nevertheless, DL and ML models can infer complex information and match the fingerprints to the pre-built fingerprint database much better than statistical fingerprinting methods. Overall, while traditional localization methods have their advantages in terms of simplicity and compatibility, they also face limitations regarding accuracy and robustness especially in complex indoor environments with obstacles and signal interference.

The disadvantages of traditional indoor localization methods has led to the exploration of more advanced and hybrid approaches in indoor localization research such as data-driven and Deep Learning-based (DL-based) methods. Data-driven and especially DL-based indoor localization methods offer several advantages over traditional approaches. Firstly, these methods leverage large-scale datasets and machine learning algorithms to extract complex patterns and relationships from the data, enabling more accurate and precise positioning. They can adapt to the unique characteristics of different indoor environments, mitigating challenges posed by signal propagation, multipath effects, and environmental dynamics. Secondly, data-driven and DL-based methods have the potential to handle multi-modal sensor data, incorporate contextual information, and fuse heterogeneous data sources, leading to improved localization performance. Additionally, these methods can continuously learn and improve over time, allowing for adaptive and robust indoor localization in dynamic environments.

Despite the advantages dl-based localization methods, they have several notable drawbacks. Firstly, these methods often require a substantial amount of labeled training data, which can be time-consuming and resource-intensive to collect and annotate accurately. Additionally, although powerful processors have become much more accessible, DL models are still computationally demanding and require substantial time and processing resources. Moreover, the black-box nature of DL models limits their interpretability, making it challenging to understand the reasoning behind localization decisions. DL-based methods are also sensitive to the quality and representativeness of the training data, and biases or inaccuracies in the data can impact model performance and generalization. Lastly, DL-based methods may struggle with robustness in dynamic environments, where changes in sensor characteristics or environmental conditions can adversely affect their performance and reliability.

Nevertheless, a large proportion of the recently proposed indoor localization systems focus of DL and ML methods, aiming to improve the mentioned downsides that these methods have. Overcoming these challenges remains a crucial focus for improving the effectiveness and applicability of DL-based localization methods.

1.5 Generalizability of DL-based Indoor Localization Methods

Even though none of the mentioned parameters and technologies used for indoor localization provide perfect information, many of the recently proposed data-driven localization methods perform relatively well [46] on the respective testing dataset. The issue with these models is that they have been trained on a train-set collected from a specific location and at a specific time, and due to the high volatility of the mentioned parameters, the underlying distribution that the data-driven model has learned from the given train-set is certain to change when the environment changes or even with time. This means that the learned information for a specific location and time is nearly ineffective for other locations or the same location at a different time. For these conventionally trained ML models to perform well in new environments, they have to go through a complete process of training, which makes these models not be readily-deployable for new locations. Moreover, a complete training process can be very hard or even not feasible in some instances due to the limitations on resources, time, and new datasets. All these mentioned reasons render conventionally trained ML models impractical as a scalable solution for indoor localization.

Chapter 2

Related Work

2.1 Indoor Localization Using Traditional ML approaches

Numerous ML algorithms have been used for the task of indoor localization. In this section we will introduce papers that have used traditional ML methods such as K-Nearest Neighbours, SVM, RVM, Random Forests, and Bayesian classification.

2.1.1 K-Nearest Neighbours (KNN)

KNN is one the popular ML algorithms that is commonly used for localization, both for classification and regression approaches . In the classification approach, the unseen data is classified by the majority vote of its k nearest neighbors. In other words, the class that appears most frequently among its k nearest neighbors is assigned to the unseen data. In regression tasks, the unseen sample is assigned an average value calculated from its k nearest neighbors. Moreover, the Weighted K-Nearest Neighbors (WKNN) can improve KNN results by modifying the weights assigned to the K nearest points.

In [85], the authors introduced a localization system that incorporated various techniques to improve position estimation accuracy. Their system employed time domain filtering and coherence bandwidth-based dimensional reduction on the Channel State Information (CSI) data. They further utilized an enhanced WKNN, integrating kernel methods, for precise position estimation. The k-nearest neighbor KNN algorithm was employed to select K reference points with the highest similarity to the target point. The average coordinate of these selected RPs was then calculated and considered as the estimated position. The results demonstrated that the system achieved a positioning error of less than 2m in 70% of the tested data points.

To enhance the precision of WiFi-based localization, the authors in [31] employed Bluetooth Low Energy (BLE) beacons in combination with WiFi RSS measurements. They adopted a WKNN to estimate unknown locations. In their approach, BLE transmitters served as substitutes for WiFi APs in areas where APs lacked power supply, as BLE transmitters can operate on battery power. They reported a localization error of 1m and 0.77m, for the KNN model using only WiFi RSS data and the KNN model using both BLE beacons data alongside WiFi RSS data.

In [1], the authors built a two-stage localization system based on KNN. In the first stage, their algorithm aims to identify the type of environment, and in the second stage, localization is performed using KNN. They utilized RSSI alongside a hybrid feature vector of Channel Transfer Function (CTF) and Frequency Coherence Function (FCF). They concluded that a model using multiple or hybrid features outperforms RSSI-only approaches.

In an effort to reduce the substantial energy usage of Wi-Fi devices caused by frequent scanning of APs, an energy-efficient system for indoor localization named ZIL [48]. ZIL employs ZigBee interfaces to gather Wi-Fi signals. To identify Wi-Fi APs using ZigBee interfaces, the researchers devised RSSI Quantification and RSSI Normalization techniques. Furthermore, they assessed three K-NN based localization approaches with distinct distance metrics, namely weighted Euclidean distance, weighted Manhattan distance, and relative entropy, in order to enhance the precision of localization. The results showed that ZIL saved energy by 68 percent on average with competitive accuracy compared to the approach based purely on Wi-Fi interface.

2.1.2 SVM

Support Vector Machine (SVM) is a popular machine learning algorithm used for classification and regression tasks. It finds the best decision boundary, known as a hyperplane, to separate different classes of data points by maximizing the margin [21]. SVM can handle complex relationships between features by transforming the data into a higher-dimensional space using a kernel function. It is widely used for its ability to handle both linear and nonlinear data, making it a versatile and effective tool in various domains.

In [83] SVM was proposed to determine the optimal hyperplane for distinguishing the nearest neighbor training data points of a given test data point using RSS. To minimize the calibration effort required to generate a fingerprint map, they employed the Bilinear Median Interpolation Method (BMIM) while ensuring the accuracy of user localization is preserved. The authors in [86] employed SVM to introduce a system for device-free localization and presence detection using WiFi CSI data. Localization and presence detection were treated as regression and classification problems respectively. The process (presented in Figure 2.1)involved collecting CSI data, CSI data denoising, extracting features, training a presence detection classifier, establishing the relationship between CSI. Density-based spatial clustering was performed on CSI data to address noise and extract effective features. To reduce computational complexity, PCA was employed to reduce the dimensionality of the data. The authors evaluated theeir proposed model in two different settings with localization accuracies of 1.22m and 1.39m for each of the two settings. The Detection precision of over 97% was achieved for both settings.

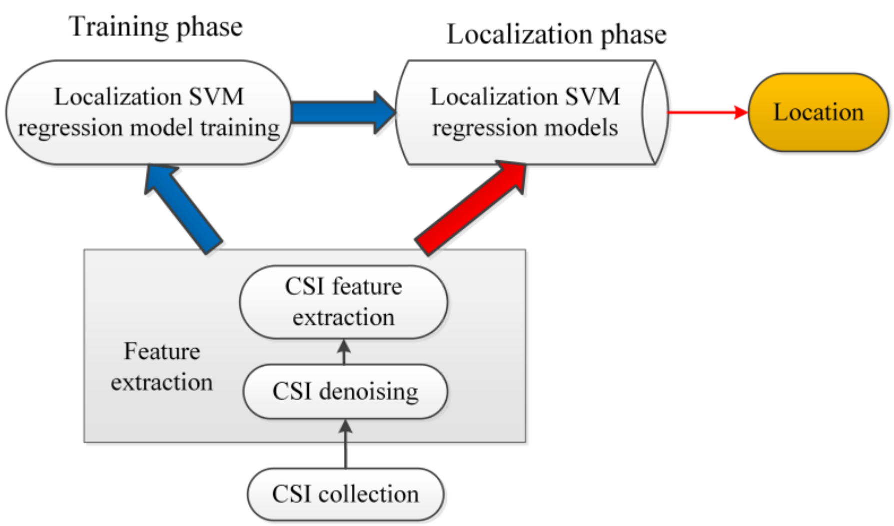


Figure 2.1: Overview of the localization algorithm used in [86]

2.1.3 RVM

Relevance Vector Machine (RVM) is a machine learning method that employs Bayesian inference to obtain parsimonious solutions for regression and probabilistic classification tasks. RVM shares a similar functional form to the support vector machine but distinguishes itself by offering probabilistic classification [59]. In [60], the authors introduced a novel approach for Ultra-Wideband

ToA localization using RVM. Their proposed model utilizes an RVM-based classifier to distinguish between LoS and NLoS signals. Additionally, they employed an RVM regressor to predict ranging errors. The authors conducted a comparative analysis between RVM and SVM in terms of NLOS identification and localization accuracy estimation. The results indicated that the mis-identification probability of the SVM classifier was 0.1143, while for the RVM classifier, it was 0.1084. In terms of localization accuracy, the RVM method achieved a localization error of less than 1 meter in 63.37% of the cases. In comparison, the corresponding percentage for SVM was 58.48%.

2.1.4 Random Forest

Random Forest [5] is a powerful ensemble learning algorithm widely used in machine learning. It combines multiple decision trees to make predictions by averaging their outputs. Each decision tree is trained on a random subset of features and data samples, ensuring diversity in the model. Random Forest is known for its ability to handle complex relationships, handle high-dimensional data, and mitigate overfitting. It provides robust predictions, feature importance rankings, and can handle both regression and classification tasks efficiently. [69] introduced a novel approach to feature extraction in complex environments for indoor localization using Random Forests. They constructed multiple decision trees and pruned them based on the root mean square error. By aggregating the votes from these trees, they obtained an estimated result. In the offline stage, they utilized the Random Forest training model as a fingerprint to design a localization algorithm, which leveraged CSI. With their method, the size of fingerprint databases just depends on the size of the Random Forest, so only a handful of information are needed to be stored so that localization can be done. This approach not only saved space but also exhibited improved performance in mitigating the impact of multipath effects. Compared to KNN and WKNN, RFFP demonstrated higher classification accuracy and lower average positioning error, making it a more effective solution.

2.2 DL-based Localization Models

This section is dedicated to introducing some of the influential DL-based indoor localization systems that have been proposed.

DeepFi [66] [67] proposes a Deep Neural Networks (DNN) model for indoor localization that uses CSI amplitude for its input. A greedy learning algorithm is used to train the model to reduce

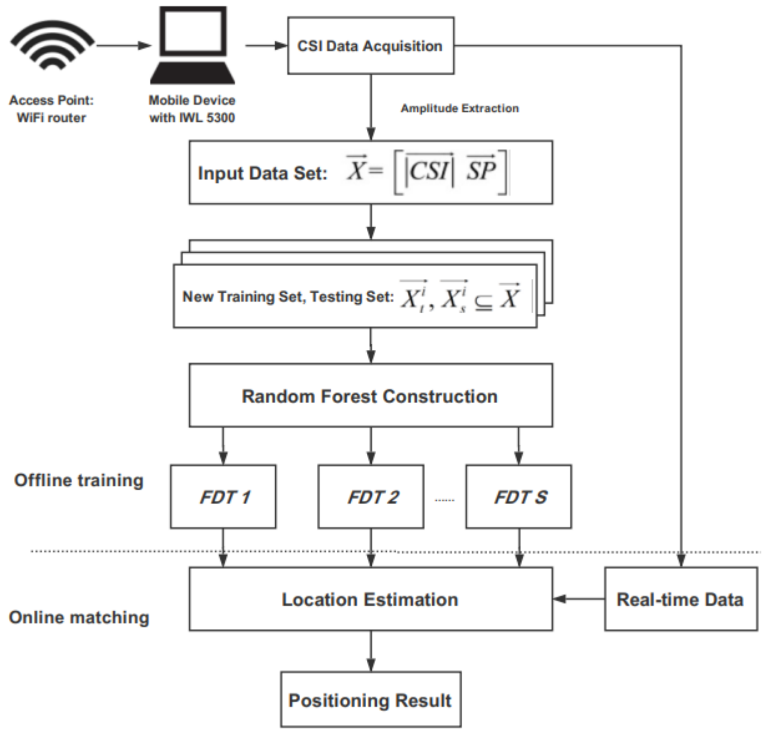
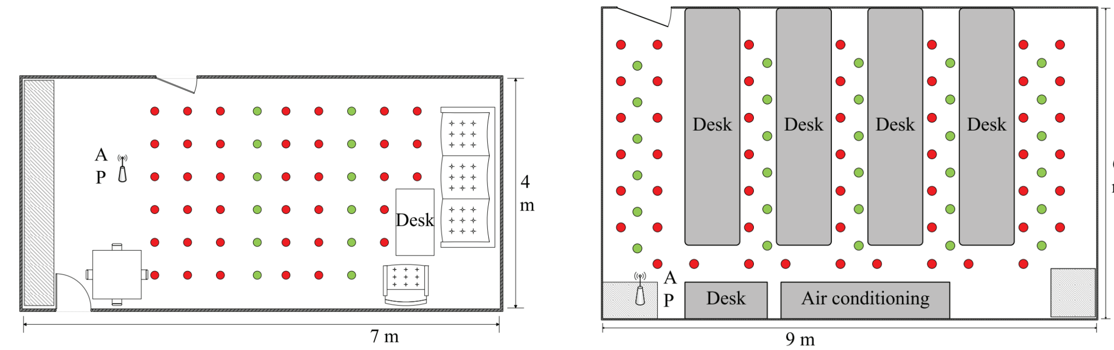


Figure 2.2: Overview of the Random Forest finger printing localization method used in [69]

the computational complexity. Finally, in the online localization phase, DeepFi uses a probabilistic method based on the radial basis function to estimate the target's location. Evaluations indicate that DeepFi outperforms traditional statistical localization schemes such as HORUS [82] and FIFS [73] with localization accuracy of 0.9425m and 1.8081m in two different environments that were tested.

In 2016, PhaseFi system [63, 64] was proposed. PhaseFi is a system that utilizes a Deep Neural Network with three hidden layers to train Channel State Information (CSI) phase data. Unlike traditional methods that treat measured data as fingerprints, the authors developed feature-based fingerprints using Deep Learning. PhaseFi employs a deep self-encoder to extract features from calibrated phase data. To reduce computational complexity, a greedy algorithm to train the Deep Network's weights layer-by-layer was used. The system achieved positioning errors of 1.08m in open indoor environments and 2.01m in complex indoor environments. The experiment layouts for the open and complex environment used in this paper can be seen in Figure 2.3

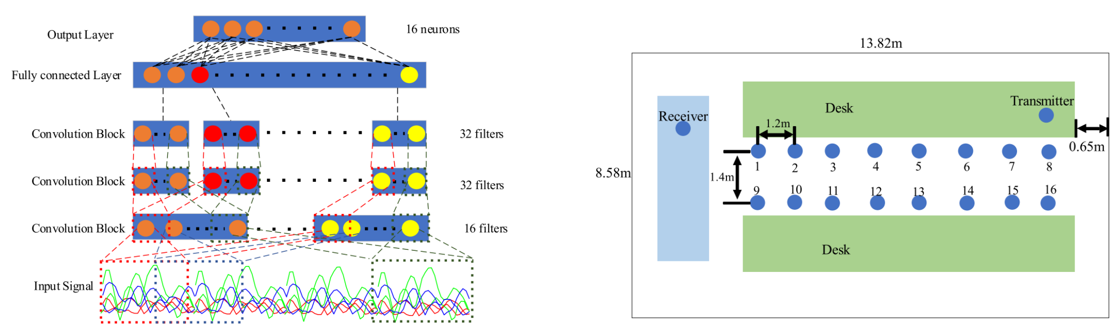
The authors in [24] compared different combinations of neural networks and input types (CSI and RSS) to determine the best system for location estimation. The study compared MLP-RSS, MLP-CSI, CNN-RSS, and CNN-CSI models. It was found that a 1D-CNN model with CSI data



(a) Open space indoor environment experiment layout (b) Complex indoor environment experiment layout

Figure 2.3: Experiment settings used in [63]

was the most effective combination in achieving accurate results while minimizing computational costs. 1D-CNN uses 1-dimensional kernels which deals with 1D data rather than 2D image data. As CSI amplitude data is also 1D, using 1D-CNN also reduces the prepossessing phase of turning CSI data into processed CSI images. The 1D-CNN system, using CSI data, achieved a maximum error of 0.92m with a probability of 99.97%. It was noted, however, that further validation with larger public datasets was necessary due to the small size of the testbed. The study utilized a testbed consisting of a room with obstacles, where 251,388 CSI measurements were collected. The authors took a classification approach to localization. They divided the room into 16 blocks and trained the system to predict the user's location within a block. An overview of the expermint settings and the proposed 1D-CNN architecture can be seen in Figure 2.4.



(a) (b)

Figure 2.4: Experiment settings and the proposed 1D-CNN model in [24]

ConFi [9] is the first localization paper that utilizes Convolutional Neural Networks (CNN). As CNNs are powerful tools for inferring information from images, ConFi arranges CSI amplitude data to create CSI feature images. 4 samples of the processed CSI images are presented in Figure 2.5. The created feature images are then fed to CNN with three convolutional and two fully connected layers. ConFi treats localization as a classification problem ,where inputs are localized based on several specified reference points. Their evaluations show that ConFi outperforms other conventional data-driven localization methods, demonstrating that CNN-based localization is a viable option.

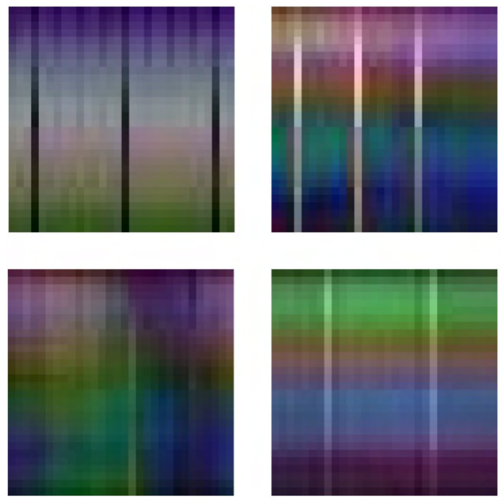


Figure 2.5: Sample of processed CSI images for 4 different reference points used in [9]. For one antenna, T CSI measurements for N subcarriers are grouped to form a N∗T matrix which turns inro a CSI image.

In CiFi [68], CSI phase data was used as a medium to calculate the angle of arrival (AoA). They used the Intel 5300 network interface card with three antennas to collect the CSI data. Based on the measured CSI phase data for every two adjacent antennas, the phase difference was obtained, from which AoA can be calculated. As AoA is not as random raw CSI phase data, it was then fed to the CNN-based localization model they proposed as an input. A sample of a preprocessed AoA image created from CSI phase data is shown in Figure 2.6. Their results show that CiFi can compete with other established localization methods, such as DeepFi, suggesting that CSI phase data can also be effective for localization.

In [51], the authors proposed a localization system that aimed to estimate the user's location using multiple Extreme Learning Machine (ELM) classifiers. ELMs are feed-forward neural networks where parameters of their hidden nodes and not just the weights need to be tuned. ELMs enable fast training for the models [25]. The proposed system employs a combination of techniques and models which can be seen in Figure 2.7. During the offline phase, the system initially utilizes principal

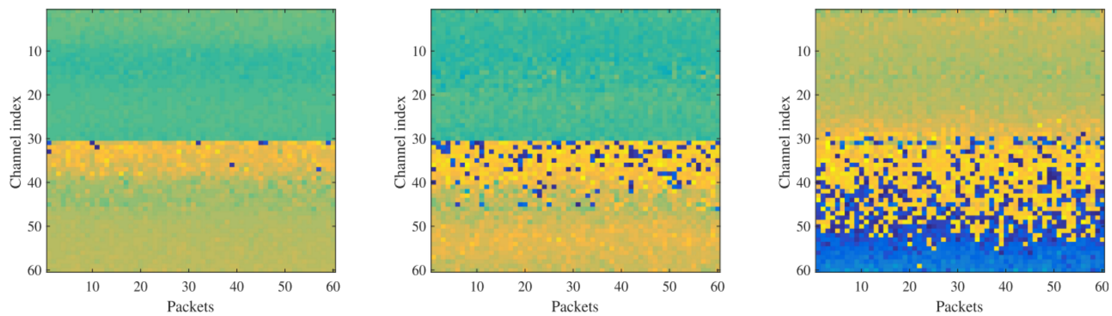


Figure 2.6: Sample of processed AoA created from CSI phase data in [68]. 2 sets of AoA data are calculated from each pair of 3 adjacent antennae at the receiver. the 2 sets of AoA data with the size 30∗60 are then concatenated to form the processed image for a reference point.

component analysis (PCA) to reduce the dimensions of the RSS data. This dimension reduction process improved the system's performance by eliminating irrelevant information from the training data. The preprocessed data are then given to an ensemble model as the input. Within the ensemble model, distinct ELM classifiers are trained for each floor to obtain individual floor-level classification results. The outcomes of all separate ELMs are then consolidated using a majority voting algorithm, to reach the final prediction of the model. During the online phase, PCA is performed again on real-time RSS data and then the processed RSS data is passed to the ensemble model. To assess the performance of their system, the authors conducted tests in a building comprising of 7 floors and 95 access points. The system was tested using 700 RSS measurements. The accuracy of the final floor-level predictions was determined to be over 96%.

The authors in [76] focused on improving the accuracy of coordinate prediction by integrating multiple data sources. Their database included geomagnetic, iBeacon, and WiFi RSS data. To process this diverse data, the authors employed a Deep Neural Network initialized with an RBM (Restricted Boltzmann Machine) [16]. Additionally, they utilized cross-validation and grid search techniques to fine-tune the neural network, while incorporating the Kalman Filter to smoothen preprocessed data to simplify the input while retaining crucial information. They approached indoor localization as a regression problem. The experiments were conducted in a testbed consisting of two interconnected rooms, spanning an area of 124 m^2. A trajectory with 15 reference points along the path was used, and 1300 groups of data were collected for each position. The results demonstrated that the system, combining the DNN and Kalman Filter, achieved impressive performance. The

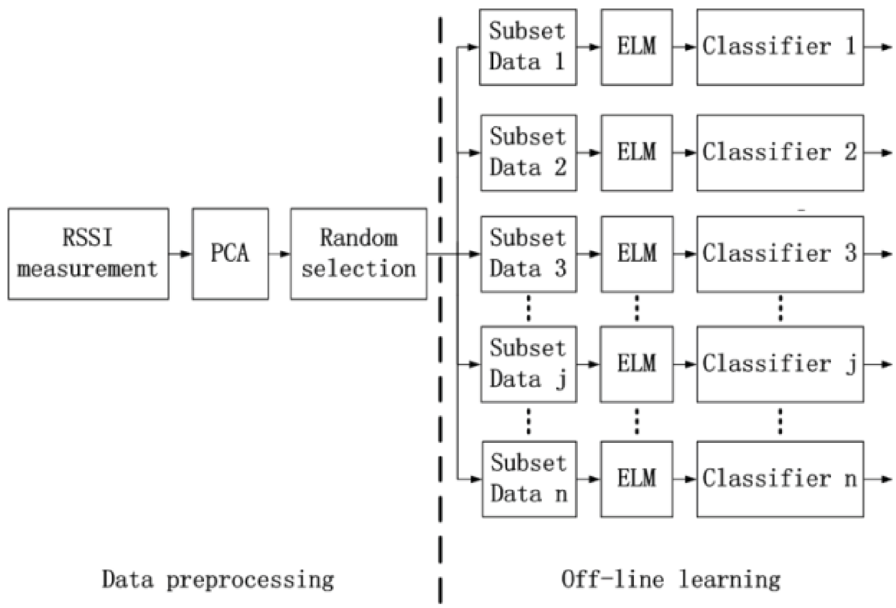


Figure 2.7: Block diagram of the localization system used in [51].

mean distance error of the system was reported to be 0.29 m, with a maximum position error of 1.59 m. In comparison, other machine learning methods tested on the same testbed achieved a best localization error of 1.26 m. Localization accuracies for models using RSS are rarely this good, suggesting that substantial enhancement in accuracy can be achieved by integrating multiple data sources.

In [58], the authors put forward an approach for indoor localization using a CNN that relies on the image representation of WiFi RSS signals. The core idea is to convert the RSS signals into 2D images, which are then processed by the neural network. The experiment involved setting up 74 reference points in a testbed, where data from 256 Access Points (APs) were collected. Each reference point's 256 RSS measurements were transformed into a 16×16 image. A sample of the created RSS images is shown in Figure 2.8. The presence of light dots in the image indicates the APs whose RSS values can be detected at that particular reference point. To enhance the input RSS data during preprocessing, they employed augmentation techniques and incorporated mean values and random numbers uniformly distributed across the dataset. This enriched dataset was utilized for training their proposed CNN architecture. In terms of performance, their model achieved a localization mean squared error of 1.44 m.

In [29] a positioning system is proposed that combines a stacked autoencoder (SAE) and

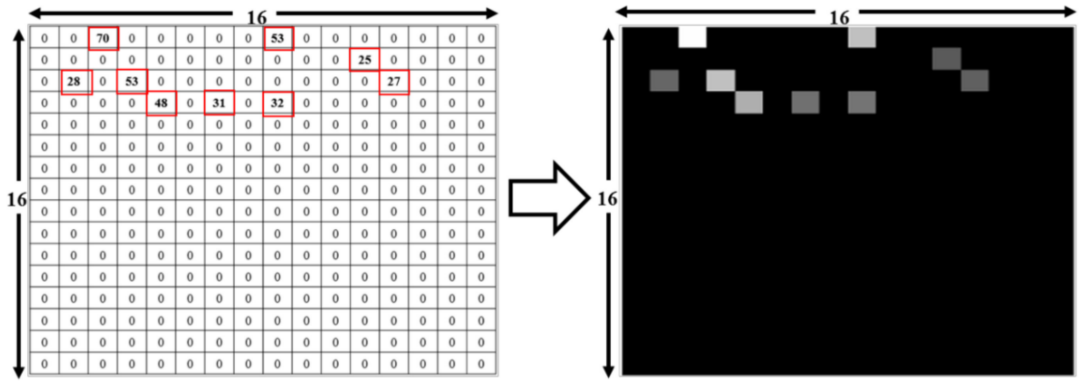


Figure 2.8: RSS data conversion to RSS images used in [58].

a DNN to estimate the user's building and floor location in indoor positioning using RSS data. Rather than predicting the building and floor simultaneously for each sample, the system tackles them separately, as illustrated in Figure 2.9. This approach necessitates the use of multiple classifiers within the indoor positioning system. To preprocess the input RSS data, the SAE is employed to reduce dimensionality and filter out noise. The resulting features are then given as inputs into seperate classifiers for building, floor, and location predictions. In terms of building and floor estimation, the system achieves 99% accuracy in building identification and a floor identification rate of 93.4%. For evaluating floor-level location estimation, they deployed approximately 200 APs and collected over 4000 RSS fingerprints. The system attains a high accuracy of 97.2% for floor-level location estimation in this specific setting. However, when applying the same system to the another dataset, the accuracy drops below 70%.

Table 2.1 provides a summary of some of the DL-based localization methods that have been proposed in the recent years. It should be noted that the presented localization errors can not be necessarily compared with each other and we can not decide which proposed method is better than the others. Different methods have been trained and tested using different datasets with different number of reference points, environment sizes, complexity of environments and obstacles, task definition (regression or classification), and granularity of reference points. Nevertheless, this table can provide a good insight into different DL-based localization systems and their performance.

Table 2.1: Summary of DL-based Indoor Localization Papers

Localization System	**Method**	**Parameter**	**Technology**	**Localization Error**
[66]	FC	CSI Amplitude	Wi-Fi	0.94m for LoS scenario 1.8m for NLoS scenario
[63]	FC	CSI phase	Wi-Fi	1.08m for LoS scenario 2.01m for NLoS secnario
[65]	AE	CSI Amplitude + AoA	Wi-Fi	1.57m for LoS scenario 2.17m for NLoS scenario
[68]	CNN	AoA	Wi-Fi	1.78 for LoS scenario 2.38 for NLoS scenario
[9]	CNN	CSI Amplitude	Wi-Fi	1.36m
[84]	SDAE+HMM	RSS	Wi-Fi	0.39 for indoor scenario
[23]	LSTM	RSS	Wi-Fi	0.75m on a collected dataset 4.2m on UJIIndoorLoc public dataset
[61]	SDAE+MLP	RSS	Wi-Fi	5.64 on UJIIndoorLoc public dataset 3.05m, 4.24m on two collected datasets
[72]	DAE+KNN	RSS	BLE	1.09m Horizontal 0.34 Vertical
[45]	VAE+DRL	RSS	BLE	4.3m
[53]	FC	RSS	Cellular	0.78m
[4]	FC	RSS	BLE+XBee+Wi-Fi	0.45
[40]	DBN	CIR	UWB	<1.5m 90% of the time

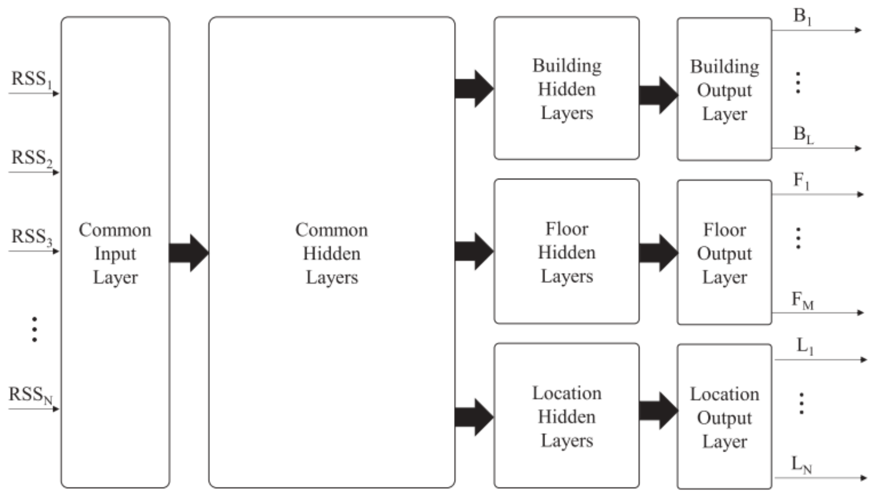


Figure 2.9: Overveiw of the hierarchical building/floor/location classification model employed in [29]. Three distinct classifiers are used to output predictions for building, floor and location. L, M, and N respectively denote the number of buildings, the maximum of the number of floors in buildings, and the maximum of the number of locations in the floors

2.3 Generalizable DL-based Localization

One fundamental issue with most of the mentioned localization models is the lack of generalizability and adaptability to new or dynamic environments, as these models have to be retrained when the environment changes to perform well. This dramatically hinders their applicability to real-world scenarios. To address this issue, a few recent works have utilized transfer learning and domain adaptation.

Transloc [34], is a knowledge transfer framework for indoor localization, which derives a cross-domain mapping to transfer the specific knowledge of one domain to another and then creates a homogeneous feature space. This enables the localization model to perform well when the environment changes with a limited number of new training data from the new environment. To increase robustness against environmental changes, Fidora [10] augments the data with a variational autoencoder to add diversity and then employs a domain-adaptive classifier to adjust the localization model to the new data.

In a recently published work, authors of [17] utilized meta-learning for indoor localization to increase the generalizability of DL-based localization models. [17] proposes a localization framework based on MAML [15] as opposed to conventional DL-based localization models. The results presented in this paper are based on simulated RSSI data. Some parameters used to generate the simulated data, such as the room size, number of reference points, and noise level, differed for each scenario, the parameters being set by pre-determined settings for training and testing scenarios separately. This was done to increase the diversity of scenarios. As RSSI is highly dependent on many parameters, such as obstacles, obstructions, and positioning, which simulations can not fully capture. Hence, the generated scenarios may not be realistically diverse. In the context of meta-learning, a lack of sufficient diverse training scenarios may lead to meta-overfitting in the model, memorizing the learning process for a handful of scenarios and not reaching generalizability for unseen scenarios.

Chapter 3

Preliminaries

3.1 Meta-Learning

Meta-learning is a subfield of machine learning that focuses on the development of algorithms capable of enabling intelligent systems to acquire knowledge from past learning experiences and improve their learning process in the future, hence, also known as "learning to learn". At its core, meta-learning seeks to build models or systems that can effectively generalize from past learning experiences to new tasks or domains, thereby exhibiting a form of adaptive intelligence. Meta-learning algorithms often operate by learning a higher-level representation or model that captures patterns and regularities across different learning tasks or datasets, allowing for the extraction of valuable insights and knowledge that can be applied to new tasks.

One prominent approach is gradient-based meta-learning, exemplified by the Model-Agnostic Meta-Learning (MAML) algorithm. Gradient-based methods optimize the model's parameters across multiple tasks or datasets, allowing the system to quickly adapt to new tasks by taking a few gradient steps. Another approach is memory-based meta-learning, where past experiences or data are stored in a memory bank and utilized to solve new tasks. Prototype-based meta-learning is one such memory-based approach that relies on the creation and utilization of prototypes, which are representations of past tasks, to guide the learning process on new tasks. In addition, there are Bayesian meta-learning methods that leverage Bayesian inference to capture uncertainty in the meta-parameters or task parameters. These methods enable more robust and principled learning in the face of limited data. Evolutionary algorithms, such as genetic programming and genetic algorithms, have also been applied in the context of meta-learning, where populations of models or algorithms are evolved to adapt to changing environments.

Meta-learning has found diverse applications across various domains in the field of machine learning. In the domain of computer vision, meta-learning has been applied to tasks such as few-shot image classification [28], where models are trained to quickly recognize and classify new classes with limited labeled examples. Meta-learning has also been utilized for tasks like object detection [71], semantic segmentation [41], and image generation [43], where it enables models to adapt and generalize to new datasets or unseen scenarios. In natural language processing (NLP), meta-learning has been employed for tasks such as few-shot text classification [78], sentiment analysis [37], and machine translation [35]. By leveraging meta-knowledge, models can effectively transfer knowledge from related tasks or domains and achieve better performance with limited labeled data. Reinforcement learning (RL) is another domain where meta-learning has made significant contributions. Meta-RL algorithms enable agents to quickly adapt to new environments, learn from sparse rewards, and acquire policies that can be generalized across different tasks. These meta-RL methods have been successfully applied to robotic control [26], game playing [8], and autonomous systems [80]. Furthermore, meta-learning has also found applications in other areas, including recommendation systems [12], drug discovery [42], and personalized medicine [33]. As meta-learning continues to advance, it holds great potential for driving the development of more intelligent and adaptable systems, contributing to the overall progress of artificial intelligence and machine learning research.

3.2 Model-Agnostic Meta-Learning (MAML)

Among the many proposed meta-learning algorithms, MAML [15] is arguably the most popular algorithm. One reason for this popularity is that, as its name suggests, MAML is model agnostic, meaning that it can be applied to any differentiable model regardless of its architecture or specific learning objective. In MAML, multiple tasks are divided into training tasks and testing tasks, and each task consists of a distinct objective, a support set (training set), and a query set (test set). In the inner loop (also referred to as the adaptation phase), the meta-learning model adapts to each task by training on the corresponding support set, followed by computing the loss function for that task on the query set. It should be noted that the outer objective function utilized in MAML for meta-learning is not the same as the objective function used for each task during the inner loop.

MAML aims to determine an initial set of parameters for the inner model, such that adapting to new tasks can be done as quickly as possible using the computed initial set of parameters. Formally, MAML considers an inner model f with a set of parameters θ denoted by f_θ.

During the inner loop, for each task $\mathcal{T}_i$, the model adapts to task $\mathcal{T}_i$ by training on the corresponding support set and, respectively, updating model parameters θ based on the inner objective function to compute θ_i'. The following equation shows the adaptation phase of a single gradient step, but it can be extended to cases where multiple gradient steps are taken, as well.

$$\theta_i^{'} = \theta - \alpha \Delta_\theta \mathcal{L}_{\mathcal{T}_i}(f_\theta) \tag{3.1}$$

where α is the step size.

The outer objective function used in the outer loop is defined as below:

$$\min_\theta \sum_{\mathcal{T}_i \sim p(\mathcal{T})} \mathcal{L}_{\mathcal{T}_i}\left(f_{\theta_i'}\right) = \sum_{\mathcal{T}_i \sim p(\mathcal{T})} \mathcal{L}_{\mathcal{T}_i}\left(f_{\theta - \alpha \nabla_\theta \mathcal{L}_{\mathcal{T}_i}}\left(f_\theta\right)\right) \tag{3.2}$$

where f_θ' is optimized with respect to the initial set of parameters θ used to adapt to each task. And the outer loop optimization rule is as followings:

$$\theta \leftarrow \theta - \beta \nabla_\theta \sum_{\mathcal{T}_i \sim p(\mathcal{T})} \mathcal{L}_{\mathcal{T}_i}\left(f_{\theta_i'}\right) \tag{3.3}$$

where β is a hyper-parameter known as *meta-step size*.

For all training tasks, the inner loop is performed, and then θ is updated during the outer loop as shown in (3.3). In contrast, only the inner loop is performed for the testing tasks to see how well the model can adapt to an unseen task using a limited support set. The pseudo code for MAML is presented in Algorithm 1.

Algorithm 1 MAML

Require: $\mathcal{P}(\mathcal{T})$: Distribution over training tasks

Require: α, β: inner step size, outer step size

Randomly initialize inner model's weights θ

while not converged **do**

Sample meta-training task $T_i \sim \mathcal{P}(\mathcal{T})$

$\theta_i^{'} \leftarrow \theta$

for all inner loop iterations **do**

Using support set $\mathcal{D}_i$ compute loss $\mathcal{L}_{\mathcal{T}_i}$

Update $\theta_i^{'} \leftarrow \theta_i^{'} - \alpha \Delta_{\theta_i^{'}} \mathcal{L}_{\mathcal{T}_i}(f_{\theta_i^{'}})$

end for

Using query set $\mathcal{D}_i'$ compute loss $\mathcal{L}_{\mathcal{T}_i}$

Update $\theta \leftarrow \theta - \beta \nabla_\theta \mathcal{L}_{\mathcal{T}_i}\left(f_{\theta_i'}\right)$

end while

Chapter 4

Proposed Method

Dl-based indoor localization solutions have shown promising results in accurately estimating the position of wireless devices in indoor environments using wireless parameters such as Channel State Information (CSI) and Received Signal Strength Indicator (RSSI). Despite their success, current DL-based indoor localization methods face challenges related to the need for extensive data, time and computational resources for training, interpretability, robustness in dynamic environments, and generalizability. Other than the issue with interpretabillity which is inherent in DL models in general, the rest of the issues are closely related to each other. A generalizable indoor localization that can perform well even in unseen or dynamic environments, would be less prone to dataset domain changes which leads to a better robustness as well. Moreover, if a model has better generalizability, it would require less or even no data to adapt to new environments, alleviating the need for extensive data and computational costs in the future. On the other hand, if an indoor localization model can only have a good accuracy on a testing set based on the training set it has observed before, it would need to go through a complete training process in order to perform well in new environments. Not being readily-deplyable in new environments, greatly reduces the applicability of the indoor localization model for practical uses.

We aim to solve the lack of generalizability in conventionally trained indoor dl-based localization models. We propose a generalizable indoor localization model using meta-learning, which can utilize the knowledge gained from training on multiple datasets collected in different environments towards new unseen environments requiring very little fine-tuning. To this end, we have collected CSI data in 33 different locations, with the data in each location constituting a separate task. We then evaluate the generalizability of the proposed meta-learning-based localization model and other benchmark methods by training on a set of the collected tasks and testing against a set of unseen tasks. Meta-learning algorithms require a sizeable amount of training tasks, which is time-consuming and challenging to collect in the context of indoor localization. Thus, we propose a data-efficient novel meta-learning algorithm, Task Biased Model Agnostic Meta Learning (TB-MAML), based on Model Agnostic Meta Learning (MAML) [15] to further improve generalizability even with relatively limited datasets. Lastly, we compare the generalizability of the TB-MAML-based localization model with other meta-learning-based localization models in terms of the number of tasks used for training.

4.1 Task Biased Model Agnostic Meta Learning (TB-MAML)

In this section, we would like to propose TB-MAML, a novel meta-learning algorithm based on MAML. TB-MAML is designed for cases with a limited number of training tasks for the meta-training process. In conventional deep learning, not having enough data samples leads to overfitting, memorization of the data samples, and consequently, not learning the underlying distribution from which the data was sampled. A similar concept called *Meta-overfitting* exists in the context of meta-learning. Consider a distribution over all tasks $\mathcal{P}(\mathcal{T})$ and a limited set of tasks $\mathcal{T}$ that do not wholly represent the distribution $\mathcal{P}(\mathcal{T})$. Suppose a meta-learning model just uses the tasks $\mathcal{T}$ for the meta-training process. In that case, it will meta-overfit to the tasks in $\mathcal{T}$, meaning that it will not learn to adapt quickly to all the tasks drawn from the distribution $\mathcal{P}(\mathcal{T})$, but just the tasks in $\mathcal{T}$. TB-MAML is designed to learn the underlying distribution $\mathcal{P}(\mathcal{T})$ even in cases where the set of training tasks $\mathcal{T}$ available to us is limited. In the context of localization, each task requires a training set and a test set for multiple reference points in a location. Since the process of collecting data for multiple reference points per each task is time-consuming, gathering a large enough number of indoor localization tasks is not an easy feat. To provide a sense of comparison, the dataset Omniglot which is a standard toy dataset for meta-learning literature has 1623 classes. If we define each task as a 10-way classification, we will have $\binom{1623}{10}$ different tasks at our disposal which we can split into meta-training and meta-testing tasks. To this end, TB-MAML is particularly valuable in the context of indoor localization as it is designed for improved generalizability for circumstances where the number of tasks is limited.

TB-MAML defines an importance vector over the available meta-training tasks to identify the tasks that push the model more toward generalizability, or in other words, the tasks that provide better information regarding the learning process of all the other tasks in $\mathcal{P}(\mathcal{T})$. TB-MAML is biased towards the more important tasks as it emphasizes them during the learning process, hence the name, Task Biased Model Agnostic Meta Learning.

To calculate the importance vector, we first select task i from the meta-training tasks. We train our inner model with the training set of task i. In a case of n-shot learning, for each task j in the meta-training tasks where $i \neq j$, we further train the inner model with the support set of task j and then test the model against the query set of task j, resulting in the loss $\mathcal{L}_i(\theta_{ij})$. We denote the average of all these losses as $\mathcal{L}_i$, which is a measurement of how well a model trained for task i can adapt to unseen tasks. By calculating the average loss $\mathcal{L}_i$ for all tasks, we form the vector $[\mathcal{L}_1, ..., \mathcal{L}_n]$. By normalizing this vector between values (-1,1) and then inverting the values, we derive the importance vector $[u_1, ..., u_n]$.

During outer loop (steps 6 and 7 in fig 4.1), when the inner loop TB-MAML has adapted to the task j using the corresponding support set, it updates θ based on the importance of task j. More Formally:

$$\theta \leftarrow \theta - (\beta + \gamma u_j)\nabla_\theta \sum_{\mathcal{T}_i \sim p(\mathcal{T})} \mathcal{L}_{\mathcal{T}_i}\left(f_{\theta'_i}\right) \tag{4.1}$$

where u_j is the importance of task j and γ is a hyperparameter that adjusts intensity of the importance vector.

The entire process of TB-MAML is summarized in Algorithm 2. Furthermore, a schematic of TB-MAML is provided in Fig 4.1 for illustration of TB-MAML. In step 1, the importance vector is computed from the training tasks available. In step 2, the inner model is initilized with weight θ, task $\mathcal{T}_i$ is sampled and the corresponding support set is fed to the inner model. Steps 3 and 4 represent the inner loop where the model adapts to task $\mathcal{T}_i$. In step 5, query set of $\mathcal{T}_i$ is given to the model and outer loop is then performed (steps 6 and 7), and the inner model's initialization weight θ is updated. After sufficient iterations when convergence is reached, meta-testing phase starts (steps 9-13). The steps taken in this phase are similar to the ones taken in the meta training phase, with the difference that outer loop is not performed.

In table 4.1, advantages and disadvantages of some of the known meta learning algorithms based on the MAML algorithm alongside the proposed TB-MAML algorithm are summarized.

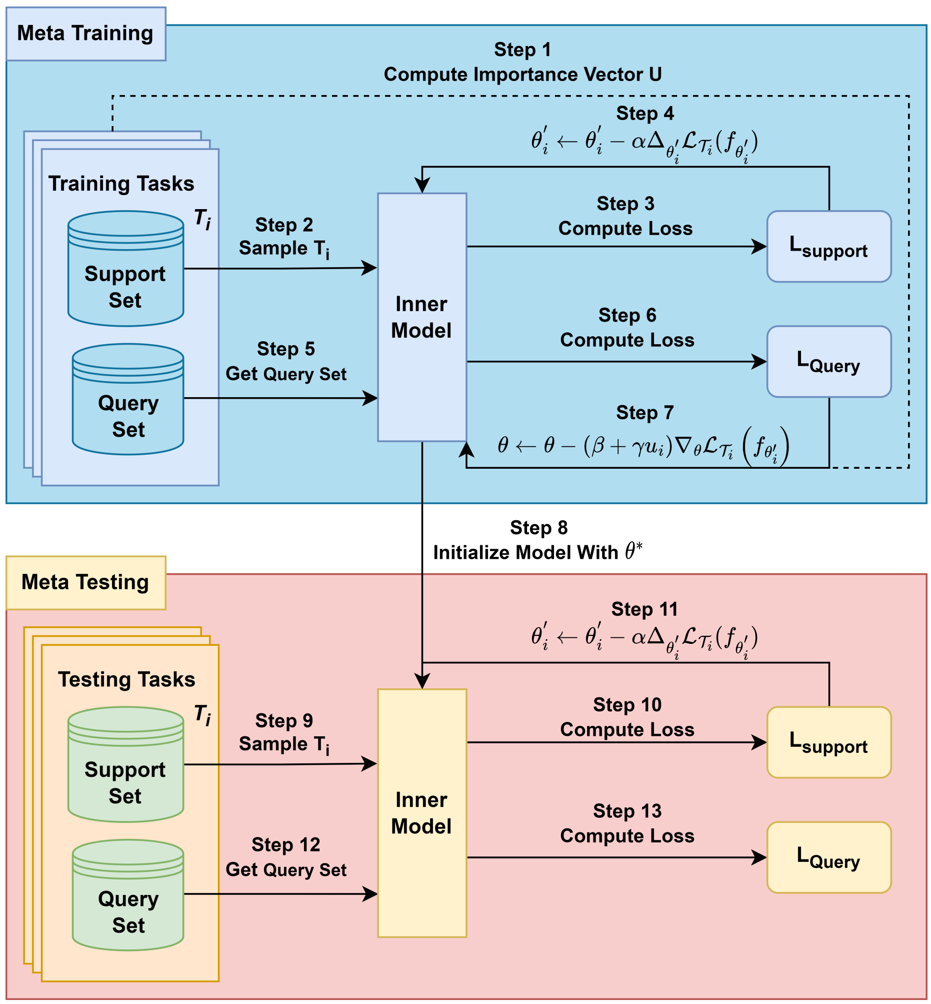


Figure 4.1: Schematic of the proposed TB-MAML algorithm.

Algorithm 2 TB-MAML

Require: $\mathcal{P}(\mathcal{T})$: Distribution over training tasks

Require: $U = [u_1, ..., u_n]$: Importance vector for training tasks

Require: $\alpha, \beta, \gamma,$: inner step size, outer step size, and importance vector intensity

Randomly initialize inner model's weights θ

while not converged **do**

Sample meta-training task $T_i \sim \mathcal{P}(\mathcal{T})$

$\theta_i^{'} \leftarrow \theta$

for all inner loop iterations **do**

Using support set $\mathcal{D}_i$ compute loss $\mathcal{L}_{\mathcal{T}_i}$

Update $\theta_i^{'} \leftarrow \theta_i^{'} - \alpha \Delta_{\theta_i^{'}} \mathcal{L}_{\mathcal{T}_i}(f_{\theta_i^{'}})$

end for

Using query set $\mathcal{D}_i^{'}$ compute loss $\mathcal{L}_{\mathcal{T}_i}$

Update $\theta \leftarrow \theta - (\beta + \gamma u_i) \nabla_\theta \mathcal{L}_{\mathcal{T}_i} \left(f_{\theta_i^{'}}\right)$

end while

Table 4.1: Comparison of Meta Learning Algorithms.

Method	Advantages	Disadvantages
MAML	Good accuracy on new tasks	High computational cost
FOMAML	Lower accuracy on new tasks	Relatively much lower computational cost
REPTILE [47]	Competitive accuracy on new tasks compared to MAML	Relatively lower compuational cost
MAML++ [2]	Good accuracy on new tasks Stabilized training Improved Convergence Speed	High computational cost
TB-MAML	Good accuracy on new tasks Better accuracy when number of training tasks are limited Less number of training tasks required	High computational cost + Cost of computing importance vector

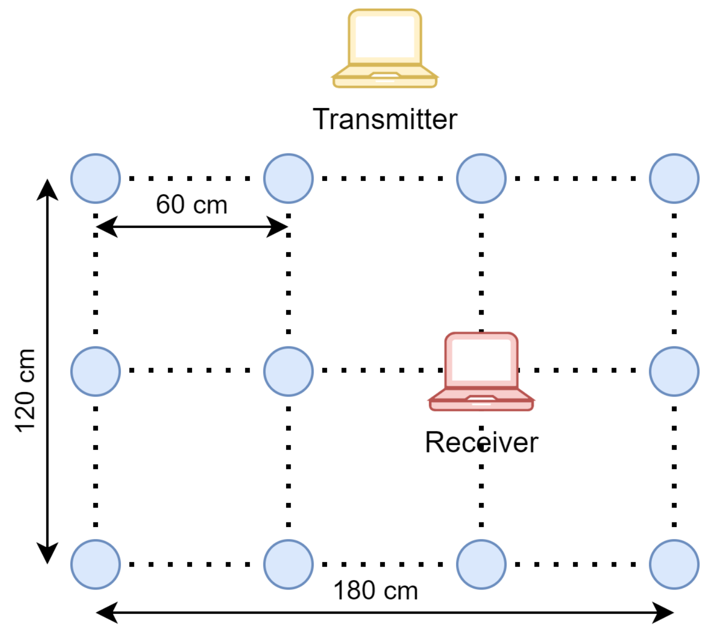
Chapter 5

Evaluations

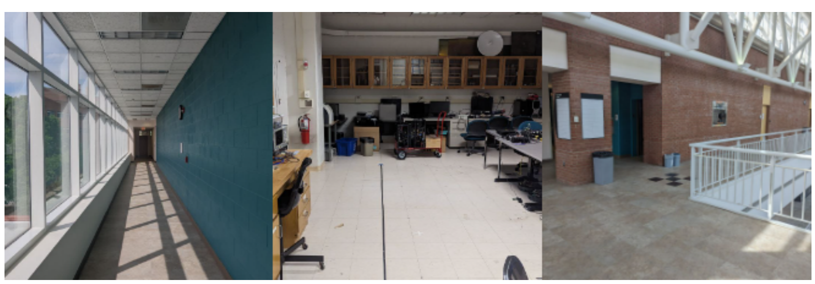
5.1 Dataset

For the purpose of testing the generalizability and adaptability of the discussed localization models, a dataset consisting of multiple different scenarios was required. In total, we collected 33 scenarios, each scenario resulting in a different task. All 33 scenarios were collected in different indoor locations such as rooms, laboratories, corridors, and auditoriums in the Fluor Daniel building and the Lowry hall building at Clemson University, to diversify the overall dataset as much as possible. A few example locations can be seen in fig 5.1(b). Each scenario consisted of 12 reference points, arranged in a 3 by 4 grid with a grid size of 60 cm. Fig 5.1(a) shows the positioning of the reference points in test scenarios. We collected CSI data for all reference points using two Intel 5300 network interface cards, one as a receiver and one as a transmitter. We transmitted Wi-Fi 802.11n packets with 20 MHz bandwidth on the 5 GHz frequency band and for every reference point. The transmitter transmits 40 bursts each of the burst includes 100 packets. To counter the instantaneous interference or fluctuations in the environment, each burst has 1 second pause time before the next one. The transmitter uses only one antenna for transmission, while the receiver uses all three antennas for receiving. In 802.11n, 52 subcarriers are carrying information and used for calculating the CSI data. The Intel 5300 card follows a grouping method that reduces the size of the CSI report field to 30. Hence, each CSI sample had a size of 3×30. We calculate and normalize only the amplitude of the CSI data before feeding it into the network[1].

[1]Dataset was collected with the help of Mr. Chunchih Lin



(a) Reference points arrangement

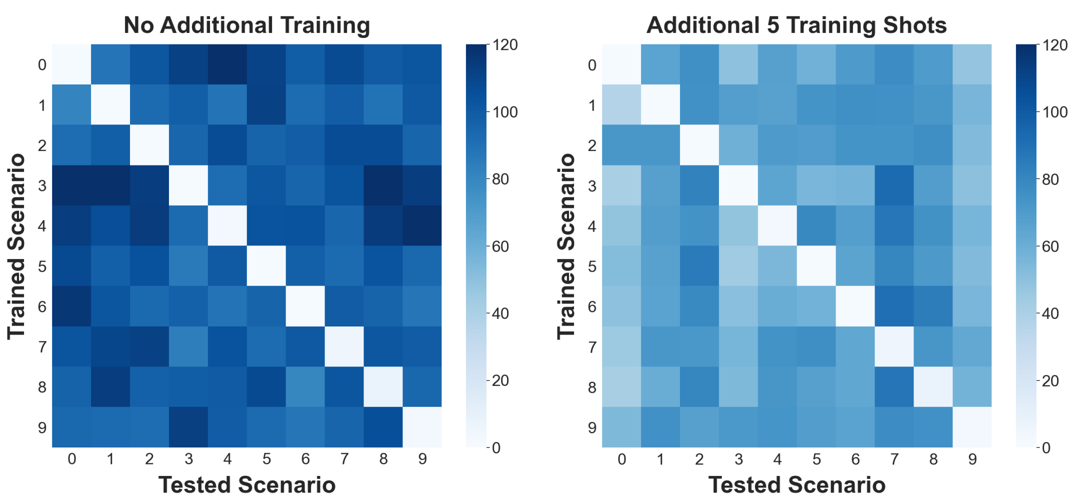


(b) Example locations of different scenarios

Figure 5.1: Experiment Settings.

Table 5.1: Structure of Inner Model

Layer	Input	Parameters	Activation Function
1D Convolution	3*30	Out Channels=10 Kernel Size=3 Padding=1	ReLU
1D Max Pooling	10*30	Kernel Size=2	-
1D Convolution	10*15	Out Channels=15 Kernel Size=3 Padding=1	ReLU
1D Max Pooling	15*15	Kernel Size=2	-
Dense	105	128 neurons	ReLU
Dense	128	64 neurons	ReLU
Dense	64	32 neurons	ReLU
Dense	32	8 neurons	ReLU
Dense	8	2 neurons	-



(a) No additional training

(b) Additional 5 shot training

Figure 5.2: Localization distance errors of a conventional DL-based localization model trained on scenario i and tested against scenario j. In Figure (a) no additional training samples from the testing scenario were provided to the model, whereas in Figure (b), five additional samples per reference point from the testing scenario were given to the model for further training. For cleaner visualization purposes, only the first 10 scenarios are considered in the figures.

5.2 Generalizability Analysis of Conventional DL-based Localization Models

Before providing the results for the proposed meta-learning models we would like to emphasize on the lack of generalizability in conventional DL localization models. Fig 5.2(a) depicts the error of a conventionally trained DL localization model on one task and then tested against another one. The architecture of the used DL model is described in table 5.1. The value in cell (i, j) is the distance error of the localization model trained for scenario i and then tested against scenario j. For cleaner visualization purposes, only the first 10 scenarios are considered in the heatmap. As it can be seen from the figure, the distance error on the main diagonal is very low (when the model was trained for scenario i and was tested against i) but for the other cases we can see the distance error is pretty high, pointing to the lack of generalizability of the conventionally trained localization model. The mean distance error in this plot is 95.98 cm.

In 5.2(b), we have the same experiment as 5.2(a) but just 5 new data samples per reference point from scenario j are provided to the localization model to train on. With a mean distance error of 63.45cm, we can observe that the overall distance error has reduced as expected in comparison with 5.2(a). But the distance error is still very high when compared to the main diagonal of the heatmap, pointing to the lack of adaptability in the conventionally trained model.

5.3 Localization Accuracy Analysis

To evaluate the generalizability of our proposed TB-MAML-based localization model, we are considering several benchmark algorithms in our experiments. The first benchmark, referred to as conventional learning, we have a localization model without prior training that has to train on a few new samples from the unseen environments. In Transfer Learning, we are feeding the full training dataset of one of the scenarios to the localization model, followed by a few new samples from the unseen target environments. We are then employing MAML, First Order Model Agnostic Meta Learning (FOMAML), and our proposed meta-learning model, TB-MAML, as cases of meta-learning based localization. It has to be noted that for all benchmarks, results are based on localization accuracies from unseen scenarios. All algorithms have been executed multiple times with different training scenarios and testing scenarios and results are averaged over the runs to reduce randomness in results. To have a fair comparison, the same inner model structure has been used for all cases which is described in table 5.1.

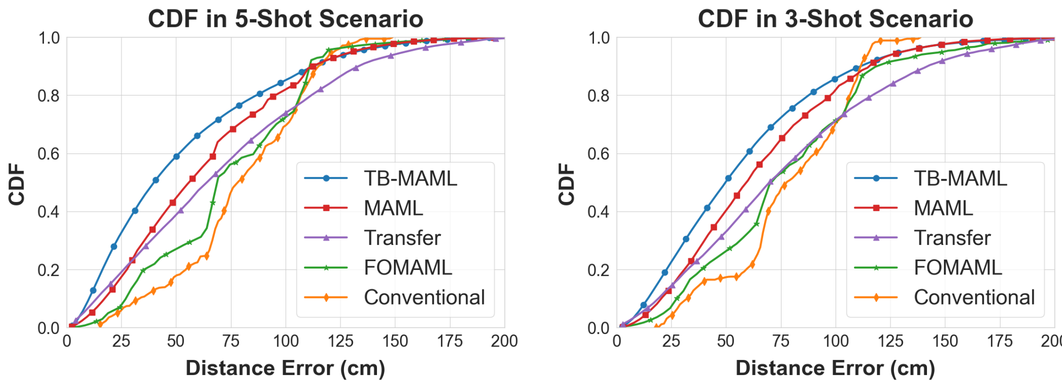
Figure 5.3 shows the localization errors of the compared localization models in terms of cumulative distribution function (CDF), in multiple cases with different number of new samples from the new scenarios. As visible from the figures, TB-MAML localization outperforms other benchmarks throughout all few-shot scenarios, followed by MAML. We can further observe that FOMAML-based localization is more accurate that a conventionally trained model, but slightly less accurate than transfer-learning-based localization. Since FOMAML is a computationally efficient first-order approximation of MAML and, therefore, a less accurate meta-learning algorithm, this observation is not unexpected. In the 5-shot case, 59 percent of distance errors for TB-MAML were below 50 cm, while the corresponding percentage for MAML, Transfer learning, FOMAML, and Conventional learning were 45, 38, 22, and 18 percent respectively. Figure 5.4 depicts a boxplot of the distance errors for the same experiments. Again, it can be observed that TB-MAML localization outperforms other benchmarks in terms of the average distance error, followed by the MAML localization model.

5.4 Limited Number of Tasks Analysis

In another experiment, we compared the accuracy of the mentioned meta-learning based localization models with our proposed TB-MAML-based localization model in scenarios with different number of training tasks. Figure 5.5 illustrates the results for this experiment. As expected we can observe that distance error of all compared meta-learning-based algorithms increases as the number of training tasks decreases. But we can also observe that TB-MAML outperforms the other benchmark localization algorithms throughout all scenarios with different number of training tasks. Moreover, we can see that TB-MAML is less affected in comparison when the number of training tasks is small (e.g. five training tasks), as TB-MAML is designed for situations where the number training tasks is limited.

5.5 Sample Efficiency Analysis

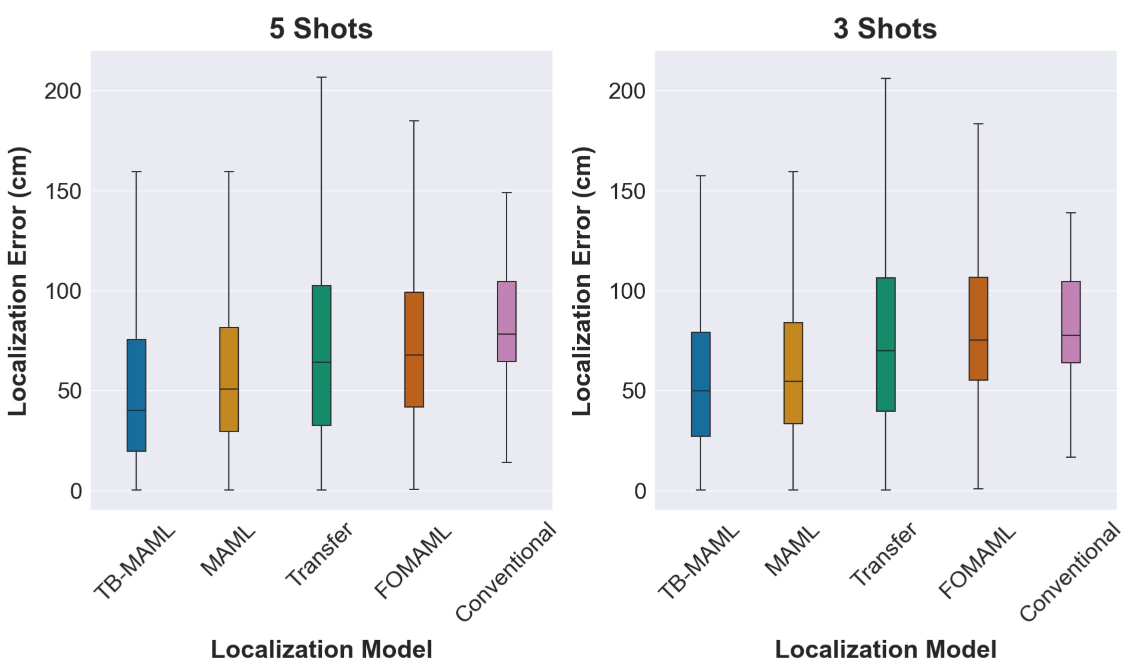
In this thesis, we claimed that by incorporating meta learning with a DL-based localization model, we are able to increase the efficiency of the localization model. In other words, we are able



(a) 5 Shot

(b) 3 Shot

Figure 5.3: CDF of localization distance errors for different localization models. Figure (a) and (b) depict cases of 5-shot and 3-shot learning respectively.



(a) 5 Shot

(b) 3 Shot

Figure 5.4: Distribution of localization distance errors for different localization models. Figure (a) and (b) depict cases of 5-shot and 3-shot learning respectively.

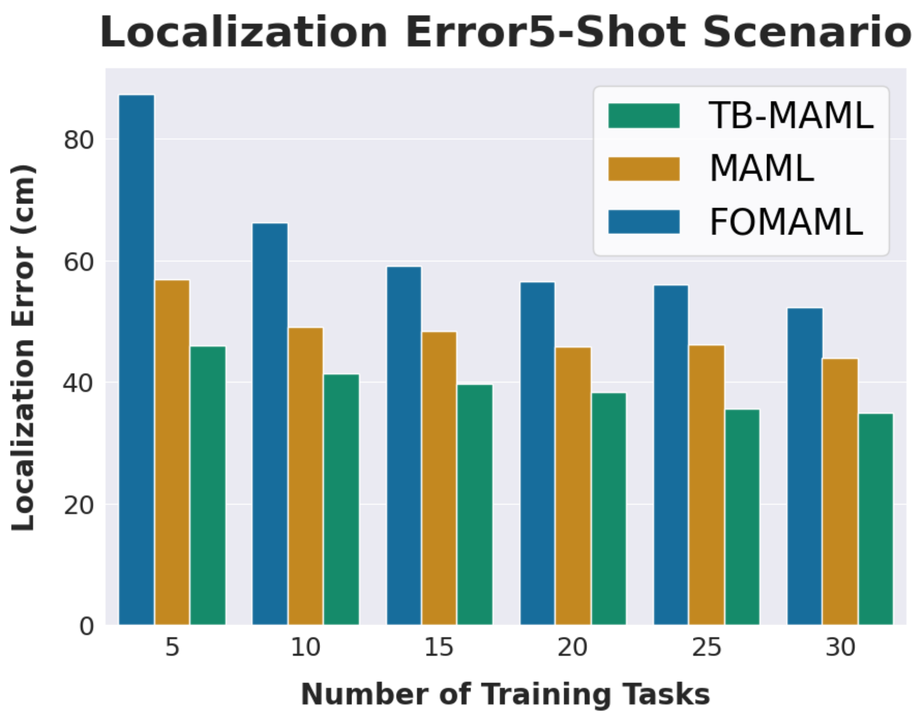


Figure 5.5: Localization distance errors of meta-learning based localization models over the number of training tasks.

to reach higher accuracy levels using less number of new training samples and hence, lower the retraining time and resources significantly, allowing the model to be applied to new environments easier. In this section we compare the efficiency of a meta learning-bsed localization model with a conventionally trained DL-bsed localization model and a localization model using transfer learning. Figure 5.6 depicts the number of shots (samples per reference point) from a new environment that are required for each of the mentioned localization models to reach a certain accuracy in the new environment. As seen in the figure, we are considering three cases of better than 70cm localization error, better than 60cm localization error, and better than 55cm localization error. The number of shots required to reach each of these localization error thresholds respectively were, 2, 5, and 7 for the TB-MAML model, 7, 12, and 19 for the Transfer learning model, and 18, 62, and 90 for Conventional DL model. We can see that by using the proposed meta learning method, we can make a conventional DL-based localization model nearly 10 times more efficient in terms of the new samples that are needed for adaptation to new environment. More over, TB-MAML is also more than 2 times more efficient than localization using Transfer Learning.

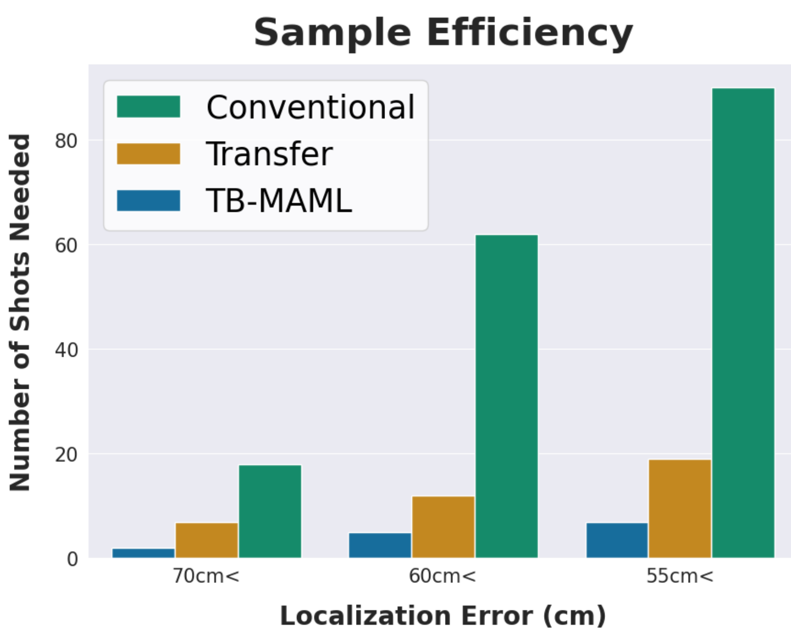


Figure 5.6: Sample efficiency of TB-MAML-based localization, conventional DL Localization, and Transfer Learning Localization

Chapter 6

Conclusions and Future Work

6.1 Conclusions

Deep learning-based indoor localization models have shown immense potential in accurately predicting the position of objects within complex indoor environments. However, most current models suffer from certain shortcomings such as challenges in interpretability , lack of generalizability and struggles with unseen environments, need for excessive data and training resources, and lack of robustness in dynamic environments. All these issues prevent the current propoed dl-based indoor localization models to become practical solutions in real-world situations.

To this end, in this thesis we focused on proposing a solution to increase generalizability in dl-based localization models. By increasing generalizability, we are also making the model more robust to dynamic environmental changes as these changes practically lead to having a new environment, and a generalizabile model can perform better in new or unseen environments. Moreover, increasing generalizability, increases data efficiency and training resources as well, as a generilizble model needs less to new training data if the environment changes.

We proposed a meta-learning-based localization model in which the localization model is wrapped around a layer of of meta-learning algorithm. Through evaluations, we demonstrated that a meta-learning-based localization algorithm can perform much more accurately in unseen environments compared to conventional deep learning localization and transfer learning localization given just a handful of new training data samples.

Meta learning algorithms require a substantial number of training scenarios to reach their full potential in generalizability for unseen scenarios and to not overfit on training scenarios. Collecting a large number of such scenarios for localization is not an easy feat. Thus, we designed a new meta-learning algorithm named TB-MAML with the focus of making the training scenarios available to us more efficient, and to enable the overall localization model reach higher generalizability with a rather limited number of training scenarios. Based on our evaluations we showed that TB-MAML localization not only outperformed conventional DL-based localization and Transfer Learning-based localization in unseen environments, but also outperforms localization models that utilize other meta-learning algorithms.

6.2 Future Work

Through the evaluations that we presented, we showed that our meta learning-based localization model can be an effective method as a generalizable localization method that can adapt to unseen environments, but there are still places for further improvement that can be addressed in future studies.

6.2.1 Flexible generalized indoor localization

The current model being put forward operates on the basis of a fixed grid space with a rectangular shape, a configuration applied uniformly in all train and test scenarios. While this approach is advantageous when dealing with scenarios featuring consistent topologies across various environments, its practicality becomes constrained when applied to different instances. The development of a localization model boasting flexibility becomes a formidable task, as it necessitates the ability to transfer knowledge seamlessly between environments characterized by diverse topological structures. Nonetheless, overcoming this challenge is paramount, as it holds the potential to significantly enhance the model's overall applicability, rendering it more adaptable to a wide range of real-world situations. This adaptability, in turn, can pave the way for the model's successful commercial deployment, unlocking novel applications and opportunities. The impact of a successful flexible DL-based localization model can revolutionize indoor localization technologies, as it will greatly diminish the biggest downside to fingerprinting DL-based localzization methods, the need for constant recallibration and retraining.

6.2.2 Decreasing the number of needed RPs data

The proposed design offers significant reductions in the number of samples and training resources required for adaptation to a new environment. However, it remains necessary to collect a few samples for each individual reference point, leading to a brief data collection phase in every new environment. To optimize this process, it is prudent to explore alternative models that demand only a few new samples from a smaller subset of reference points compared to those used in the training scenarios. This approach further streamlines the effort needed for adapting to novel environments, enhancing overall efficiency and scalability. Emphasizing this line of inquiry could yield valuable insights, paving the way for better integration of DL-based indoor localization systems into dynamic and evolving settings.

6.2.3 self-calibrating generalized indoor localization pipeline

Different environments are not necessarily environments in different locations. Changes in Obstacles, movements, interferences and even temperature could shift the domain space of the collected data which will in time result in having a different environment. Another future study could be designing a pipeline, with a data collection module that is constantly collecting data from various reference points of a location, and an online generalizble indoor localization model that keeps updating itself using the knowledge it has amassed and based on the few new samples that it is receiving from the data collection module. This design can be very effective for applications where a single location needs localization capabilities over long periods of time.

6.2.4 Standardized tests for the proposed DL-based localization systems

A diverse range of technologies, parameters, and model architectures being explored and proposed for DL-based localization models. Researchers have delved into various sensor technologies, including Wi-Fi, Bluetooth, UWB, RFID, cameras, and environmental sensors, to gather data for indoor positioning. They have employed different DL architectures, such as CNNs, RNNs, AEs, and transformer models, to process and analyze the sensor data for localization tasks. Despite this, we are not able to confidently decide which of the proposed localization systems are superior over the others as these proposed systems have been tested based on different datasets with varying characteristics. These datasets encompass differing numbers of reference points, various environment sizes, complexities of indoor spaces, types of obstacles, task definitions (regression or classification), and granularity of reference points. This variability makes it challenging to compare and identify the best solution for indoor localization. To arrive at the optimal solution, it becomes essential to conduct a series of standardized tests under precisely the same settings, enabling a fair and conclusive evaluation of the proposed models' performance.

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