Survey On Indoor Localization

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ABSTRACT

In the past decade, much research has been done on indoor localization. Why is this the case? Wouldn't humans just use GPS signals indoors as we use them outdoors for navigation?

The purpose of indoor localization and outdoor localization is the same. However, we need to find different ways of tracking indoors due to weak GPS signals. The purpose of localization is to track objects or people. Some of the categories of techniques are beacons, Wi-Fi signals, leaky wave antennas, and human tracking techniques.

The information collected about the techniques comes from top conferences such as MobiCom, Mobisys, and NSDI conferences. These categories have their pros and cons. An overall view is that Bluetooth signals are cheaper to implement than Wi-Fi techniques due to the cost difference between beacons and access points. From the papers, it can be concluded that Wi-Fi signal techniques are more precise and less prone to errors than Bluetooth signal techniques. This is because Bluetooth low energy errors are around meters and Wi-Fi signal techniques can go under centimeters for errors.

KEYWORDS

Channel State Information, Deep Learning, Convolutional Neural Network, Bluetooth Low Energy, Dispersion Effect, Wi-Fi Signals, Access Points, Leaky Wave Antennas

1 Blue Tooth Low Energy

One of the systems that uses Bluetooth low energy (BLE) is Mloc. The paper introduces this system Called "Experience: Practical Indoor Localization for Malls". Mloc is a smartphone-based indoor localization system that uses Bluetooth low energy. They also use geomagnetic field (GMF) strength as a fingerprint to enhance the accuracy given by the BLE RSSI. This paper was at the conference of ACM MobiCom of 2022. Mloc has already been deployed in China since 2018. This research is about a more extensive evaluation of the system. Mloc is being used by one million customers in China and is deployed in seven cities covering around 152 thousand m^2. The system uses two fingerprints, the BLUE and GMF. The system has two phases which are offline training and online inference. In offline training the system pays humans to go around the mall to collect BLE from different spots and online inference is where the customers' smartphone collects BLE to help with navigation. The first step in implementing this system is to deploy the BLE Beacons in the mass.

Figure 1: BLE Beacon deployed on the ceiling

The distance between each beacon is around 10 to 15 meters. However, since there are large errors in atriums and dead ends, the distance between beacons in those areas is placed 6 meters apart.

In the training data step, the researcher pays human workers to collect BLE and GMF fingerprints around the area of the store. The first step of tracking is to find the initial position of the user. This is found using building identification, floor estimation, and localization estimation. Building identification is found using BLE beacon IDs. Floor detection is defined using the 5 strongest BLE signals. The localization estimation uses the algorithm called K nearest neighbor. This algorithm finds the BLE fingerprints that are closest to the fingerprint collected at the current location. The system uses k =20 which uses 20 fingerprints to estimate the area.

The next step is online location tracking. This is found using the navigation technique called Dead Reckoning (DR). DR uses base position and measurements of the object's speed and heading to predict the object's position. The system also uses Particle filtering (PF) based tracking which is used to localize the user.

However, there are some drawbacks, the failure rate is around 4.9% for beacons. This failure is attributed to the battery in the beacons and how some beacons fall off the ceilings. The researcher of this system tells us that Mloc does better in small malls than in larger malls. Errors are also noticeable in the systems where the median error is 2.4m which is considered a big error. This could go unnoticed because, in the malls, the lowest width of a store is 5 meters.

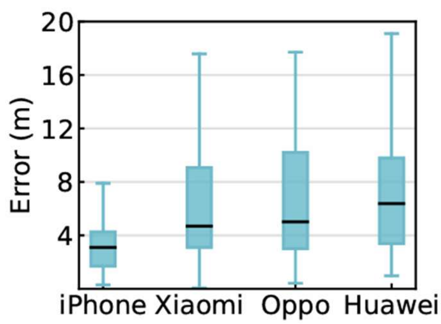

Figure 2: Localization error across smartphone brands

Another huge problem with this system is that it does significantly better if you are using an iPhone than other phones. For example in Figure 2, we can see that the median error for other phones is higher and they also have higher variance. This is because of different software and hardware. The researcher has noted that phones such as Huawei customize Android for energy-saving purposes and this caused degraded localization accuracy.

2 Wi-Fi-based indoor Localization techniques

There are many different Wi-Fi-based indoor Techniques. Top conferences show systems like Dloc, LocAP, and Bifrost. Comparing Wi-Fi and Bluetooth techniques, we can see that Wi-Fi techniques have a way smaller error than Bluetooth. However, it is more expensive to implement. Wi-Fi-based indoor positioning techniques use Wi-Fi signals emitted by a smartphone and collected by the Wi-Fi access points to convert these signals into location estimates. All the listed systems use channel state information for localization. These CSI consist of things like angle of arrival, time of flight, and antenna geometry.

Starting with the system called Dloc, it relies on a mapping system and a positioning system. It said that this system is a data-driving approach where it can improve indoor localization performance when there are reflectors and obstacles. The mapping system maps the physical map of the open space of the location and the positioning system is used to track the current position in that open space from using CSI.

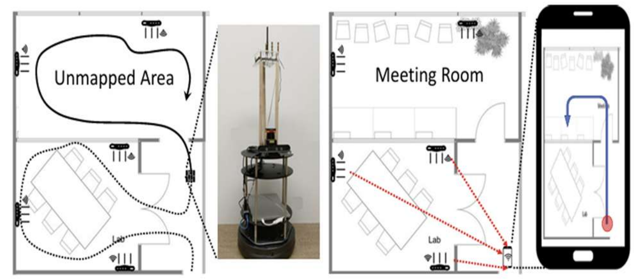

Figure 3: Overview of DLoc

Dloc uses an automated mapping platform called MapFind. MapFind is a robot equipped with A LIDAR and odometers to use simultaneous localization and mapping(SLAM) to create indoor maps without human intervention. A Wi-Fi device is also attached to the robot to generate data for training. Figure 3 shows what Map Find bot looks like and its path in collecting data. As you can see access points are deployed which will be useful in collecting CSI. The systems will first convert wireless signals received from the access points and transform this into channel state information like the angle of arrival and time of flight. However, there is trouble when a line of sight is blocked. This is solved by using a neural network to build an implicit model of the environment. Then the model can be used to identify the location of unlabeled points.

Dloc uses deep learning research with the usage of convolutional neural networks and 2D image-based techniques in indoor tracking. The channel state information is translated into 2D heatmaps and is inputted into the neural network and the output is the location of the target. Collecting data is easier said than done. Deep learning approaches often require large amounts of training data to be accurate and work. As we said before, MapFind collects the data and often it will collect training samples in 20 minutes for a 1500 sq ft open space. This will allow the deep learning model to predict their location when given the signals from the user's smartphone.

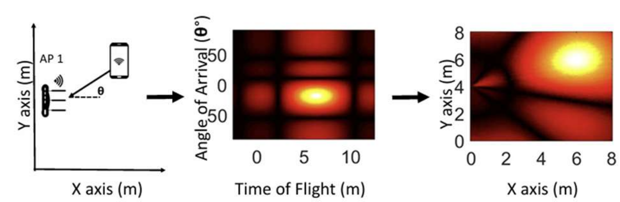

Figure 4: Input representation of channel state information

Figure 4 shows the 2D heatmaps used as input for deep learning. The system achieves a median accuracy of 65 cm. There are some limitations such as the mapping speed by the robot for DLoc. If we scale this to a larger area like a mall, how long will it take to map the area? This technique has trouble in a bigger environment.

LocAP is another system that was introduced. It is an autonomous system to psychically map the environment and locates the channel state information. First, they deploy access points around the indoor area. Then, it uses a robot to collect channel state information just like Dloc with LIDAR attached. The CSI in this system is the antenna geometry. The point of this system is to estimate access point location attributes which are access point location, antenna placements, and deployment orientation. The process is called reverse localization. Like Dloc, LocAP uses simultaneous localization and mapping) robot to get the CSI from AP. The systems are similar, but they differ in algorithms and models. LocAP uses art localization and SLAM algorithms.

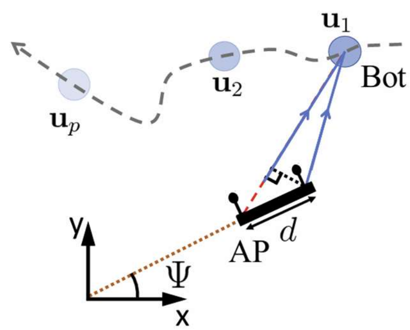

Figure 5: Relative Geometry Prediction.

LocAP focuses more on antenna placement and geometry prediction. Once each AP in the area is calculated with its location, they will instantly give the user their location. Its median error is 5 cm which the researcher says is well below the threshold. The researchers are focused on 3D models later in the future to help LocAP improve to the next level.

Bifrost is another system that uses Wifi signals for localization. However, it uses a different technique of Wifi from Dloc and LocAP. The main mission of the Bifrost system is to provide sufficient line-of-sight signals for localization. It uses the dispersion effect of signals transferred from the leaky wave antenna(LWA) that is deployed. LWA can receive signals from access points and radiate these signals into different frequencies toward directions. This enables frequency and spatial division multiplexing (FSDM). Bifrost uses two LWA to transform Wifi signals into FSDM signals. This will help the target to only receive a unique type of frequency. This system is represented in Figure 6. Something similar is that it also uses channel state information such as angle of arrival like Dloc and LocAP

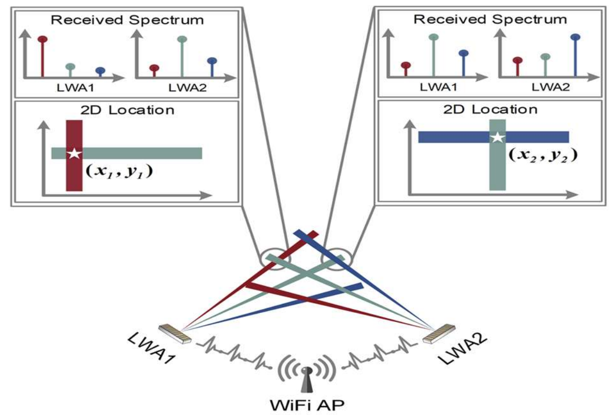

Figure 6: Principle of Bifrost system

One advantage that this method has over Dloc and LocAP is that it is cost-effective and easier to use. LWA is cheaper than Wifi AP and easier to deploy. The results are compared to another system called SpotFi. From data collection, we can see that the Bifrost system has fewer notable errors than the SpotFi system in Non line f osight areas. Again, the purpose of Bifrost is to improve in non-line-of-sight areas. Objects such as chairs, furniture, and even people block these areas contributing to the loss of signals. However, SpotFi does have fewer errors when there is a line of sight.

These systems all have the same kind of purpose which is to manipulate wif signals to get CSI and to use models or algorithms to detect the target location.

3 Human-based indoor Localization

There are sometimes issues for delivery platforms to keep track of the status of couriers in real-time locations in an indoor environment. For example, in real life, we can track the real-time location of our packages. However, this is difficult indoors because of the lack of GPS signals. TranLoc is a system that uses predictive models without extra action like deploying beacons and AP. The system will use existing data from delivery platforms like progress reports and course trajectories. Transloc aims to predict couriers' behaviors and localization.

The first thing is the order progress report data from delivery platforms. These are collected since a courier must report when the order is accepted, arrived, picked up, and delivered. TranLoc uses this information to create an inference on the current position of the courier.

Algorithm 1: Symbolic Graph Construction

Input: Matrix X, Matrix Y, threshold α
Output: Mobility Graph

T_x, T_y : walking time matrices;
$T_p(p)$: walking time on path p; P as an empty path set
Sort all the nodes by T_x and store in a min-heap H.
A = $H.pop()$, $P.add(Path(Entrance, A))$
while H *is not empty* **do**
    next = $H.pop()$
    $min\_p = argmin_{p \in P} |T\_x(next) - T_p(p) - T_y(p.tail, next)|$
    $min\_err = |T\_x(next) - T_p(p) - T_y(p.tail, next)|$
    if $min\_err < \alpha$ **then**
        new_path = $min\_p + next$
        $P.add(new\_path)$
    else
        $P.add(Path(Entrance, next))$

Figure 7: Symbolic Graph Algorithm

Figure 7 shows the algorithms that help predict the correct real-time location by converting spatial algorithms into a temporal inference problem. The thing to note is that this system also uses Bluetooth Low Energy to detect when couriers are near merchants. This helps with the evaluation of indoor location and delivery time.

4 Conclusion

In the past decade, indoor localization has been a hot topic. Many systems have been brought to our attention. These include techniques like BLE and Wi-Fi signals and they have been improving. For example, Mloc was introduced in 2017 while improved systems were tried in 2021. It's good to see that Mloc is being used by more than 1 million customers in China. There are also other different methods of indoor localization such as human techniques. For example, the system Transloc focuses on previous courier progress reports to analyze the location of future couriers delivering packages efficiently

Although we have a lot of systems that are being introduced at top conferences, these systems still need to be improved. For example, for Mloc, the median error is in meters which is quite unacceptable if you are trying to locate smaller things such as items in a store. Further to say that Mloc results show that it has trouble dealing with Android devices such as Huawei.

There is a reason why we have not seen a large amount of indoor localization techniques deployed in the environment around us. There are a lot of problems with scalability. As we can see these systems require deployment of some kind to achieve these techniques. Items such as beacons, access points, and antennas require a lot of money. For example, beacons are deployed 8 meters apart for the system to work correctly. If that’s the case, we need to deploy tens of thousands of beacons to suffice the system. We also must provide maintenance of some kind. This is why we haven’t seen many real-life indoor localization systems deployed.

We hope to see that someday in the future, some kind of indoor localization system will be deployed. This will make shopping easier, such as localizing items.

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