Towards CSI enabled Closed-loop WiFi based SLAM

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Abstract

Autonomous Robots, VR and AR are becoming increasingly popular in indoors, because of which there has been immense research in alternate sensor modalities to achieve low cost and cm-accurate simultaneous localization and mapping (SLAM) algorithms. While there exist inside-out SLAM algorithms that do not need external deployment, they accrue errors over time, leading to high error SLAM systems. On the other hand, there are outside-in systems that claim mm-accurate localization systems but are easily prone to errors due to blockage by user movement. Moreover, they are expensive to deploy on large scales. In this poster, we present the tools to perform both outside-in and inside-out SLAM together and achieve a perfect loop closure using WiFi as an additional sensor. First, we present an outside-in bot localization algorithm, DLoc, that achieves high accuracy even in the corner cases of NLOS, unlike existing WiFi indoor localization algorithms. Then we present the inverse problem of solving for accurate WiFi access point locations and geometries and our solution of LocAP, which solves accurate AP infrastructure in a given environment which is similar to the existing inside-out SLAM approaches like Landmark optimization. Thus in our poster, we present and demo our work of LocAP and DLoc and show how they complement each other in closing the loop by borrowing the best of both the worlds to achieve low-cost and sub-cm-accurate SLAM algorithm.

1 Introduction

Indoor systems like AR/VR systems today depend on two forms of tracking. *Inside-out tracking*, which involves feature matching using onboard sensors, can fail if the VR/AR headset moves too fast or if the environment is feature-sparse. *Outside-in tracking*, which employs external sensors (eg. HTC Vive [1]), constrain the users to small 5m x 5m environments and needs expensive infrastructure deployment. Another problem, in the outdoor setting of Advanced Driver Assistance Systems (ADAS), is the failure of LIDAR and cameras in foggy and stormy weather [9]. Both these problems can be solved using wireless (WiFi for indoor/5G NR for outdoor) localization and tracking. Unfortunately, the current wireless localization and tracking systems fail to achieve the required degree of accuracy at tracking and navigation in both indoors and outdoors. A key reason is the abundance of multi-path and non-line-of-sight scenarios in Indoor scenarios and poor signal quality in outdoor scenarios. Another reason is the lack of a closed-loop tracking system (which utilizes both inside-out and outside-in tracking) in the current wireless localization systems. Furthermore, current systems are cumbersome to deploy and do not provide accurate localization within the context of the map.

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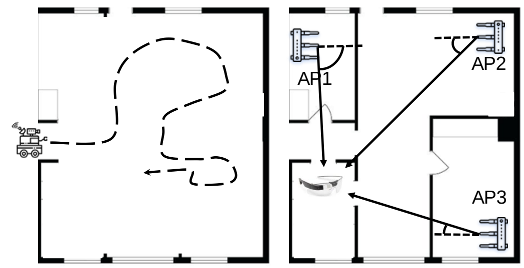

(a) Infrastructure Mapping (b) Context and Localization

Figure 1: **Implementation of LocAP and DLoc (Left)** An unknown environment with unknown AP attributes and unknown environment, where LocAP is deployed first. **(Right)** Once LocAP is deployed and mapped initial locations of AP, DLoc and LocAP are used in tandem to correct for each other to achieve low-cost sub-cm accurate SLAM.

We would like to tackle this issue by utilizing a Graph SLAM architecture [4] which combines both inside-out and outside-in tracking and label it *closed-loop* SLAM. We hope to provide sub-cm-level localization, with the context of a map, in both outdoor and indoor scenarios.

To achieve this closed-loop SLAM, we need two main moving parts – *forward localization* and *reverse localization*. Forward localization provides the global estimates of the user device, given the positions of the access point. Whereas, reverse localization contrasts this measurement, by providing estimates for the access points and their antenna geometries. Reverse localization furnishes these measurements given the channel measurements from a contiguous set of user locations. Immediately, we can see how the two can work together to bolster each other's predictions. In the following text, we will describe our work in developing a unique forward localization algorithm, DLoc [3] and a reverse localization algorithm, LocAP [2].

Firstly, for *forward localization* we present DLoc[3], a learning-based user localization technique that achieves state-of-the-art user localization. There has been a lot of research in the past two decades in indoor WiFi-based user localization [5, 7, 8] that has achieved decimeter level indoor user localization. None of these algorithms tackle the problem of the more prevalent NLOS scenario when there is no direct line of sight path from the transmitter to the receiver. In DLoc, we firstly tackle this NLOS scenario by learning-based ap-

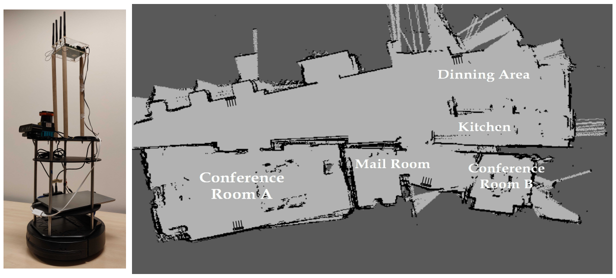

Figure 2: **Robot deployment: (Right)** We deploy both of our systems (DLoc and LocAP) on the bot shown above so as to demonstrate the working principal of WiFi based closed-loop SLAM algorithm.**(Left)** An example map generated by the bot deployed in an unknown environment.

proaches, where we have an autonomous bot that explores an already mapped space, to cover sufficient diversity of training data to train our deep neural network model. Thus by training for a given mapped space, DLoc achieves to accurately tackle the NLOS scenario and achieves state-of-the-art decimeter level localization performance for 90th percentile datapoints.

With the help of *forward localization* we have achieved the robustness of outside-in tracking of localization, but are still vulnerable to errors in the anchor points that locate the user. Unlike *forward localization*, there is little research in *reverse localization* or accurately locating the WiFi access points. So we present, LocAP[2], which accurately locates the WiFi access points (APs) and their antenna geometries/placements to within a few mm of median error. In this work, we first present the stringent requirements on the location and antenna placements on the AP and show that one needs to be able to (a) locate the access point within sub-10cm accuracy, (b) estimate the relative displacement of each antenna on the AP accurate to sub-cm, and (c) the deployment orientation of the AP to less than 10^o of error. We then show a novel differential phase difference based algorithm that achieves these requirements by smart combining techniques. LocAP solves accurate AP location and antenna geometry on the AP thus performing the inside-out tracking.

Thus we achieve the best of inside-out robustness using LocAP and outside-in accuracies using DLoc, which we can then use in a closed-loop Graph SLAM architecture to achieve mm-accurate user localization and environment mapping.

2 Deployment

Both of our systems are deployed a bot that is an autonomous robot equipped with LIDAR, RGBD camera, gyroscope and odometer to navigate an environment. We use the publicly available RTAB-Map SLAM framework[6] to create an accurate 2D occupancy grid map as shown in Fig 2(left). Furthermore, given a descriptive map of the environment, these frameworks also provide the locations of the bot.

To achieve autonomous navigation, our bot works in two stages. Firstly with the user's aid, it navigates the environment. In this stage, SLAM works by capturing data from these sensors and combining this data into an accurate map of the environment. Next, during the autonomous data collection phase, the bot uses this map to match features it has previously seen before to accurately localize itself in real-time. It then collects location associated with *reverse localize* the WiFi AP infrastructure and also explore the environment to collect training data for DLoc. We then use these initial estimates of the WiFi APs and the trained DLoc model to initiate our loop for optimizing the closed-loop Graph-SLAM architecture defined. We would like to present and demonstrate the working of our two systems during the poster session for the same.

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