WiFi Assisted Loop Closure Detection

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Abstract. In indoor environments, LiDAR based SLAM can have potential cons, due to the computational efficiency and featureless parts of environment. One way of approaching this issue is integrating some other types of sensors or available data. In our approach, we are trying to use WiFi data, to reduce computation time and make SLAM independent of geometry of the environment. Each pose of the robot will be assigned one WiFi fingerprint, and based on their similarity loop closures can be determined. Since WiFi data is fluctuating due to the different reasons, simple similarity comparison is not enough and we are trying to implement fingerprint sequence-based approach, which would take neighbouring poses of the current poses for which we are trying to estimate whether they are loop closures. Reliable loop closures, using WiFi data, can be found in very fast and simple manner. Besides having only WiFi SLAM, integration into existing LiDAR SLAM is possible as well, improving the efficiency and preserving the accuracy of that SLAM system.

Keywords: SLAM · Loop Closure · WiFi Fingerprint

1 Introduction

Simultaneous Localization and Mapping (SLAM) is crucial for robots in unknown environments, but GPS isn't available indoors. LiDAR and cameras are common sensors, but they face challenges in large areas and geometrically-degraded spaces. Our project explores using WiFi signals to address these issues. Comparing WiFi signals is faster than scan matching, and WiFi fingerprints improve loop closure detection accuracy in challenging environments. In this project we will outline our WiFi loop closure detection approach, share results, and discuss potential enhancements.

2 WiFi fingerprint similarity

Each WiFi fingerprint represents a list of Received Signal Strength (RSS) values from all visible Access Points (APs) for a given node. To detect loop closures, we rely on the similarity between these WiFi fingerprints. However, WiFi signals are not always reliable due to fluctuations, making it essential to use fingerprint similarity as a condition for selecting loop closure candidates. In the next chapter, we will discuss how to filter and identify true loop closures from these candidates.

The similarity between two fingerprints, denoted as $\mathbf{f}_i$ and $\mathbf{f}_j$, can be computed using the following formula [2]:

$$\mathrm{sim}(f_i, f_j) = \frac{H}{L_i + L_j - H} \cdot \frac{1}{H} \cdot \prod_{n=1}^{H} \exp\left(-\frac{(f_{i,n} - f_{j,n})^2}{2\sigma^2}\right) \tag{1}$$

Here, L_i and L_j represent the total number of visible APs at their respective timestamps, while H represents the number of common APs visible at both timestamps.

However, this similarity function has an issue. When there are many commonly visible APs (i.e., a high value of H), the product term in the formula can become very small, approaching zero. This issue is illustrated in the figure below:

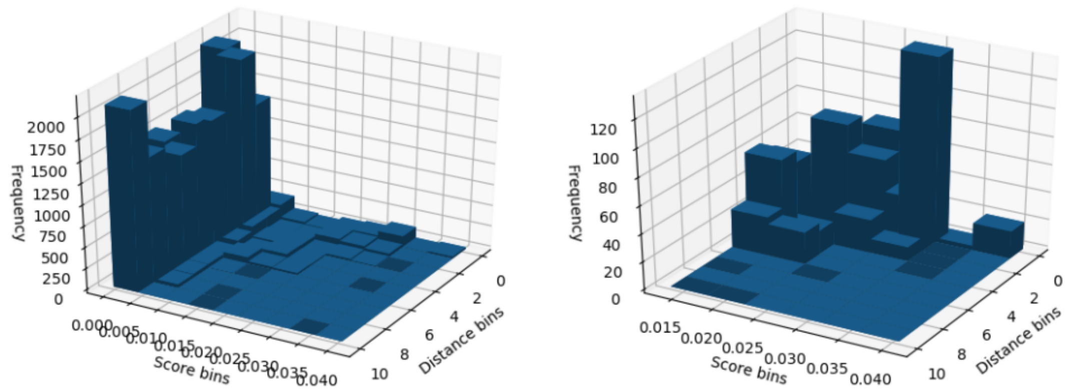

Fig. 1: Similarity score distribution

To address this problem and make the similarity score less dependent on the number of common APs, we have modified the function as follows:

$$\mathrm{sim}(f_i, f_j) = \frac{H}{L_i + L_j - H} \cdot \prod_{n=1}^{H} \exp\left(-\frac{(f_{i,n} - f_{j,n})^2}{2\sigma^2}\right)^{\frac{1}{H}} \tag{2}$$

This modification ensures that the similarity score remains robust and is not overly affected by the number of common APs.

3 Loop Closure detection using WiFi

Due to WiFi signal unpredictability, loop closures cannot rely solely on fingerprint similarity scores. We use a "sequence-based" approach:

1. Nodes $\mathbf{x}_i$ and $\mathbf{x}_j$ with high similarity scores are loop closure candidates.
2. Create windows of width w around nodes $\mathbf{x}_i$ and $\mathbf{x}_j$.
3. Determine the best relative transformation by minimizing the cost function:

$$\mathbf{T}^* = \frac{1}{w} \cdot \sum_{w/2}^{w/2} \mathrm{dist}\left(T(x_i^{-1} \cdot x_{i+\tau}), x_j^{-1} \cdot x_{j*}\right) \tag{3}$$

   where correspondences x_{j*} to the nodes in track i are calculated via:

$$x_{j*} = \frac{1}{\sum_{l=1}^{k} \mathrm{sim}(f_{i+\tau}, f_{\pi(l)})} \cdot \sum_{l=1}^{k} \mathrm{sim}(f_{i+\tau}, f_{\pi(l)}) \cdot x_{\pi(l)} \tag{4}$$

   After having those correspondences, optimal transformation can be solved by applying the Iterative Closest Point (ICP) algorithm with known correspondences.
4. Assess loop closure based on Mean Squared Error (MSE).

This approach ensures reliable loop closure detection. After obtaining loop closures, we have the whole pose graph constructed and we would need to optimize it[3].

4 Data Collection

4.1 Tools Used for WiFi Fingerprinting

In the process of collecting data for Wi-Fi fingerprinting, various tools were utilized, each with its own strengths and limitations. Firstly, iwlist provided a basic snapshot of available Wi-Fi networks but lacked real-time updates. In contrast, airodump-ng was a powerful tool for real-time monitoring, continuously updating information about nearby Wi-Fi networks and devices. Pywifi, a Python library, offered flexibility but required manual polling for monitoring. Lastly, nmcli, the NetworkManager Command-Line Interface, had a slower update rate. The choice of tool depended on project-specific needs, with airodump-ng being ideal for real-time monitoring, while iwlist, pywifi, and nmcli could be useful in simpler scenarios where real-time updates were not critical. The key is to select the tool that aligns with the project's objectives and monitoring requirements for effective data collection and analysis.

4.2 Robot Platform

Our data collection process was efficiently supported by the $Nimbro_home$ platform, which includes the Tiago Robot as the mobile platform. We used an Ouster Lidar - OS Dome 64 Channel with an integrated IMU to capture high-resolution point cloud data and inertial measurements for Simultaneous Localization and Mapping (SLAM) tasks using CLINS. To assess the impact of wifi-based loop closures, we integrated a USB Wifi Receiver into our platform to collect wifi fingerprinting data at each timestamp during experiments. Additionally, we employed a Brio Fisheye Camera to capture fisheye imagery, which can be used as a reference for future performance comparisons.

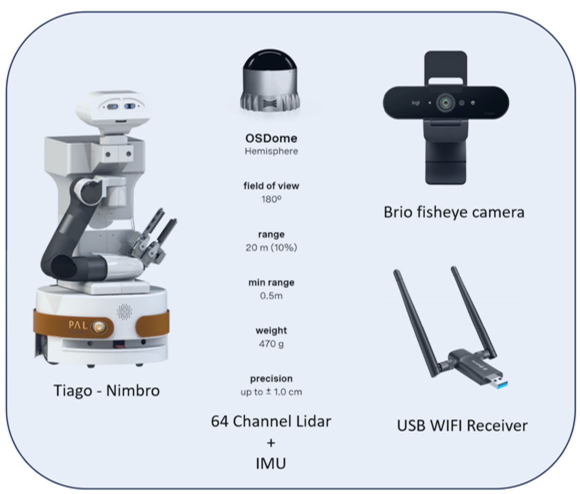

Fig. 2: Data Collection

4.3 Robot Environment

Our data collection was conducted within the confines of our project lab, located at Friedrich-Hirzebruch-Allee 8, 53115 Bonn. The lab's layout and characteristics naturally encouraged the formation of diverse loop closures of varying sizes, making it an optimal environment for conducting SLAM experiments. This choice of location allowed us to create a dataset that encompasses a wide range of real-world scenarios and challenges, enabling comprehensive evaluations and validations of our SLAM algorithms and methodologies.

Fig. 3: Robot environment

5 Results

5.1 WiFi Signal Quality and Distance Estimation

One crucial aspect of our data analysis involves assessing Wifi Signal Quality and its impact on distance estimation. We observed that Wifi signal strength does not follow a consistent pattern, particularly in scenarios where multipath interference and line-of-sight (LOS) conditions vary. To address this issue, we explored the Free Space Path Loss (FSPL) model for distance estimation under clear LOS conditions. The FSPL model is expressed as follows:

$$FSPL(dB) = 20 \log 10(d) + 20 \log 10(f) + K \tag{5}$$

where d is distance from router to the receiver, f is frequency of the router and the k is constant dependent on the units used for d and f.

For our specific units of kilometers for distance (d) and megahertz for frequency (f), the formula becomes:

$$FSPL(dB) = 20 \log 10(d) + 20 \log 10(f) + 32.44 \tag{6}$$

However, it's important to note that this formula may not always provide accurate distance estimations due to several factors, including a significant frequency difference between low-frequency Wifi fingerprinting (1 Hz) and Lidar frequency (10 Hz), resulting in multiple poses for the same signal strength, as well as unexpected results in cases of non-LOS conditions and multipath interference, as visualized using Open3D, which consistently showed that the estimated distances calculated with the FSPL model tended to underestimate the actual distances, particularly in scenarios with prevalent multipath interference and non-LOS conditions.

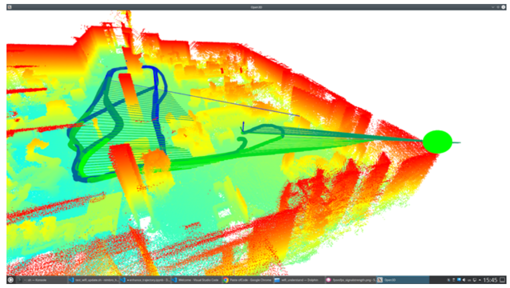

Fig. 4: Distance estimates for time stamps 0-60 seconds

These findings underscore the need for caution when relying solely on Wifi signal strength for distance estimation in complex and dynamic environments. While the FSPL model can provide reasonable estimations under LOS conditions, its accuracy diminishes in scenarios with multipath interference and non-line-of-sight conditions.

5.2 Assessing WiFi Fingerprint Stability for Loop Closure Detection

To use WiFi fingerprints for loop closure detection, we conducted experiments by repeating a looping trajectory in our lab four times to observe signal strength changes upon revisiting locations. We noticed periodic signal strength behavior but not exact numerical matches due to dynamic factors such as scene changes and robot orientation affecting the WiFi receiver's orientation. While periodicity showed potential for loop closure detection, we acknowledged the dynamic nature of WiFi fingerprinting, emphasizing the importance of considering these variations in our loop closure algorithms, particularly through the exponential component in similarity calculations between fingerprints.

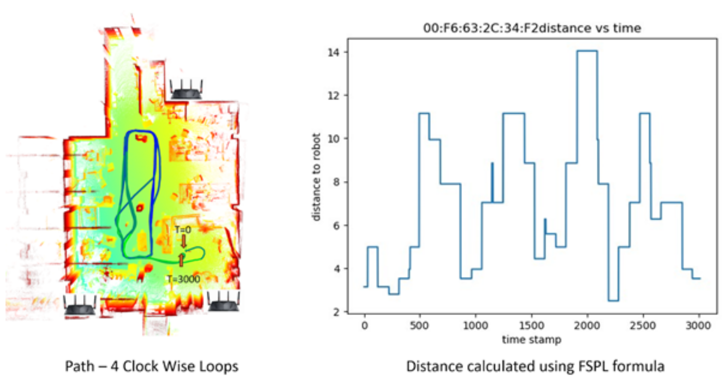

Fig. 5: Distance for one MAC address

5.3 Evaluating Similarity Scores for Loop Closure Detection

For Wifi-based loop closure detection, we compared similarity scores between a specific fingerprint and others collected along the same trajectory, revealing a recurring pattern but inconsistent high scores. Unlike Lidar-based SLAM, which typically uses a fixed threshold for loop closure, we faced challenges due to variations in similarity scores across sequences and difficulty in identifying a universal threshold, given the dynamic nature of Wifi fingerprints influenced by environmental changes and robot orientations.

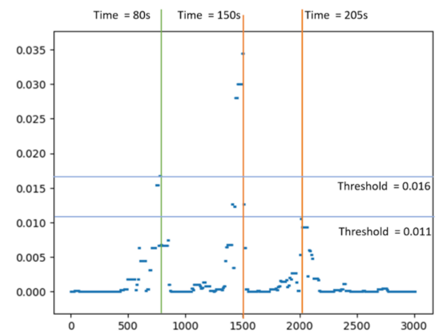

Fig. 6: Similarity score between timestamp 1500 and all other timestamps

5.4 Controlled Experiments for Wifi-Based Loop Closure Detection

To rigorously evaluate our Wifi-based loop closure detection method, we conducted controlled experiments due to suboptimal results from real-world data, as shown in figure 7.

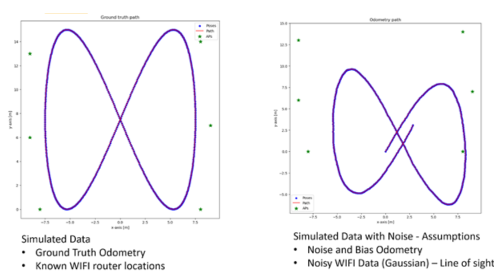

Fig. 7: Simulated data

In these simulations, we introduced noise to both trajectory and wifi fingerprint data to test the method's robustness. Our approach comprises two stages:

1. **Identifying Possible Loop Closure Candidates**: This stage identifies potential candidates based on similarity scores, enabling us to determine a consistent threshold value across various scenarios, sometimes achieving perfect scores of 1, as shown in figure 8.

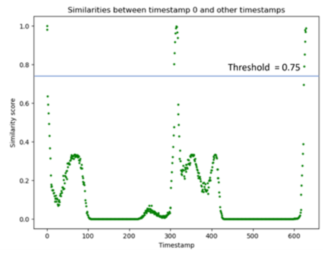

Fig. 8: Similarities between timestamp 0 and other timestamps

2. **Refining Valid Loop Closure Candidates**: In the subsequent step, we narrow down candidates to valid loop closures and determine their relative transformations using a Singular Value Decomposition (SVD)-based Iterative Closest Point (ICP) method.

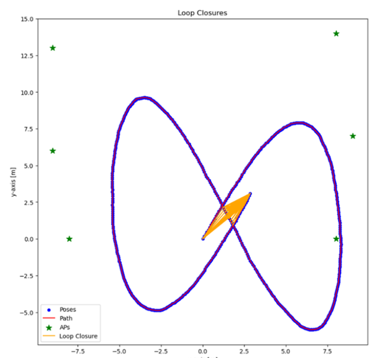

Fig. 9: WiFi Loop Closures on Simulated Data

These controlled experiments, as illustrated in the plot, allowed us to assess the method's reliability and robustness, ensuring its effectiveness for real-world Wifi-based SLAM applications. Additionally, we experimented with varying the window size for estimating loop closure validity and transformation, finding that a window size of 20 consistently yielded the lowest average Root Mean Square (RMS) error, as shown in figure 10.

Window Size	Average Error (GT – Estimated transformation)	N(Loop Closures)
6	2.25m	61
12	1.65m	51
20	1.13m	84
30	1.14m	61

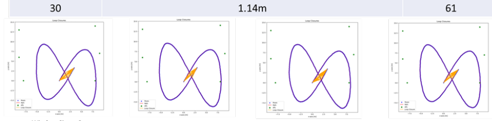

Fig. 10: WiFi Loop Closures and different window size

5.5 Testing on Real Data

In the conclusive phase of our Wifi-Based Loop Closure Detection method evaluation, we transitioned from simulated data to real-world assessments. This real-world testing involved the creation of a new dataset, covering the entire ground floor of the Friedrich-Hirzebruch-Allee 8 building, with a carefully designed trajectory that necessitated successful loop closures for a return to the initial point. We incorporated the initial trajectory estimate from the CLINS pipeline and employed it in conjunction with wifi fingerprints for every pose. This integration allowed us to systematically identify possible loop closure candidates. Our results, visualized through figure 12 showcasing these candidates, affirm the practical effectiveness and reliability of our method in real-world scenarios. While we did not succeed in establishing a systematic method for determining the correct threshold for similarity, in the final case, we resorted to using an arbitrary number as a threshold as shown in the figure 11. This evaluation represents a significant milestone in Wifi-based SLAM, emphasizing the potential for further refinement and application.

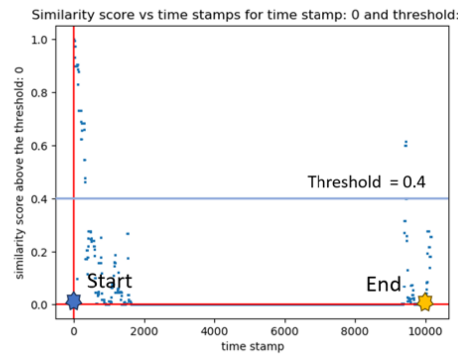

Fig. 11: Similarity score: timestamp 0 vs rest

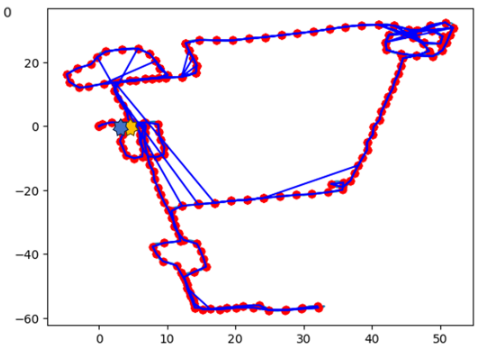

Fig. 12: Loop closure candidates detection using WiFi fingerprint similarity

6 Conclusion and future work

In summary, our exploration of Wifi-based SLAM has yielded valuable insights into its potential and challenges. While we haven't proposed specific solutions, our research represents progress in understanding Wifi-based SLAM. Our experiments in controlled and real-world settings demonstrate the promise of Wifi-based loop closures for expediting pose graph optimization. Notably, we modified the similarity score calculation method to enhance results.

As we look ahead to future work, our focus remains on adaptable threshold determination mechanisms and further exploration of pose graph optimization and its integration into SLAM systems, such as CLINS.

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