Indoor Wireless Beacon Tracking Using ESP32

Gautam Singh, G.V.V. Sharma

Indian Institute of Technology Hyderabad, India

Email: cs21btech11018@iith.ac.in, gadepall@ee.iith.ac.in

***Abstract*—This document is a report which demonstrates the use of machine learning in beacon tracking using an unmanned ground vehicle (UGV) and a WiFi-enabled microcontroller such as the ESP32.**

1 Introduction

Positioning, localization and navigation (PLAN) technology has become an essential capability for consumer electronics and autonomous vehicles alike. This fast growing market has seen the entry of big tech giants such as Amazon, Apple and Google. Use cases of PLAN include safety, medical applications and assistance for the elderly and the specially abled. Reliable PLAN technology can reduce road accidents, congestion, energy and time consumption. However, many existing PLAN technologies cater to industrial use cases and are expensive, complex and require hardware that might be scarcely available to consumers.

To overcome the above challenges, we propose a simple, effective and robust algorithm for indoor beacon tracking using a single WiFi or BLE beacon and a low-cost easily available microcontroller such as the ESP32 that is suitable for consumer electronics such as robot vacuum cleaners. The main contributions of this paper are as follows.

1) A simple yet robust algorithm for indoor beacon tracking using only RSSI measurements from a single target beacon.
2) A practical implementation of the algorithm on an ESP32 microcontroller mounted on a UGV chassis using open-source frameworks such as PlatformIO.

The remainder of this paper is organized as follows. In Section 2, we present a brief survey of related work in the field of indoor beacon tracking. In Section 3, we present the mathematical formulation of the problem and the key concepts used in our approach. In Section 4, we present the implementation details of the algorithm on the ESP32 microcontroller. In Section 5, we present the experimental results and performance evaluation of our proposed approach. Finally, in Section 6, we conclude the paper and discuss possible extensions of our work.

2 Related Work

A comprehensive survey of PLAN technology presented in [1] categorizes PLAN technologies based on the primary sensors used in navigation and illustrates the trade-offs between accuracy, cost and complexity. Some of these technologies are briefly described below.

The authors of [2] present a fuzzy controller system consisting of three ultrasonic sensors and one camera to detect obstacles in the robot's vicinity. The navigation logic is implemented on a BLE tag module using the angle of arrival (AOA) method and is suitable for unmanned nursing in hospitals, especially during pandemic outbreaks. The authors of [3] propose iDROP, a 3-D localization scheme for drones in indoor GPS-denied environments that is robust against noise and multipath fading and provides location estimation with high accuracy. The authors of [4] present a UGV powered by the robot operating system (ROS) that uses light detection and ranging (LiDAR) for accurate navigation even in dynamic conditions, suitable for various indoor robotic use cases such as in warehouses or construction sites. The authors of [5] present a scalable navigation system for ESP32 microcontrollers using multiple BLE beacons. A neural network is employed to model the position of the robot based on the signal strength received from various BLE beacons and the Levenberg-Marquardt method is used to accurately estimate the position of the robot. The authors of [6] present a strategy for landing a UAV using a radio beacon that exploits a special structure occurring when approaching the target beacon from above to reduce the flight time required for landing near the beacon.

Methods based on artificial intelligence (AI) have gained popularity in recent literature. The authors of [7] propose an easy to implement method for multi-object tracking (MOT) using an encoder-decoder mechanism. Their proposed method achieves comparable performance with state-of-the-art frameworks on the challenging MOT dataset. The authors of [8] leverage deep reinforcement learning (RL) to train an agent for tracking dynamically moving objects using unmanned surface vehicles (USV) in marine environments. The trained RL agent performs comparably to the analytically derived trajectory in the steady state. The authors of [9] explore multiple RL algorithms using LiDAR inputs on TurtleBot3, showing that the twin delayed deep deterministic policy gradient (TD3) is the most efficient and robust across varied environments.

Many of the above methods are either too complex or too expensive to be implemented on cheap hardware such as an ESP32 microcontroller. Furthermore, a lot of supporting infrastructure needs to be set up to enable autonomous navigation. Our work aims to provide a lightweight and cost-effective solution for indoor beacon tracking using easily available wireless-capable microcontrollers such as the ESP32. It builds upon the proposed algorithm in [10].

3 Preliminaries

To estimate (radial) distance to beacon, we use its signal strength. For WiFi, this is the **Received Signal Strength Indicator** (RSSI). The RSSI (in dBm) at radial distance of r metres is given by

$$R(r) = R(1) - 10\log_{10}(r) \tag{1}$$

where $R(1)$ is the RSSI at a distance of 1 metre from the beacon. The beacon tracking problem can be formulated as the following optimization problem.

$$\max_r R(r) \quad \text{s.t. } r > 0. \tag{2}$$

The derivative and second derivative of $R(r)$ is given by

$$R'(r) = -\frac{10}{\ln 10}\frac{1}{r}, \tag{3}$$

$$R''(r) = \frac{10}{\ln 10}\frac{1}{r^2} > 0. \tag{4}$$

Notice that for $r > 0$, $R'(r) < 0$, thus $R(r)$ is a decreasing function of r. This implies that the maximum RSSI is at $r = 0$, as expected. Since $R(r)$ is a convex function of r, we can use gradient ascent to recursively find the point where the RSSI is maximum, which would correspond to the location of the beacon. Using (3), the gradient ascent update equation is given by

$$r_{n+1} = r_n + \alpha R'(r_n) = r_n - \frac{10\alpha}{r_n \ln 10} \tag{5}$$

where r_i is the radial distance at the i-th step and α is the step size. Since $r_n > 0$, we can see that $r_{n+1} < r_n$ for all n. In other words, the radial distance to the beacon is decreasing with each step. This means that the UGV will converge towards the beacon. However, due to the explosion of the gradient in (3), the update steps become larger as r_n decreases, which could lead to overshooting the beacon. To prevent this, the UGV uses a recursive algorithm to update its position using this principle until it is close enough to the beacon based on the RSSI measurements it takes at various points in the vicinity of its current position. The algorithm is described in Algorithm 1.

Algorithm 1 Beacon Tracking Algorithm

Input: RSSI threshold T, number of steps N

```
while GetRSSI() < T do
    Take N steps in a straight line and measure the RSSI at each step.
    Suppose the maximum RSSI is measured at step i.
    Move to the position at step i
    if i = N then
        Move one step forward.
    else if i = 0 then
        Move one step backward.
    else
        Turn left.
```

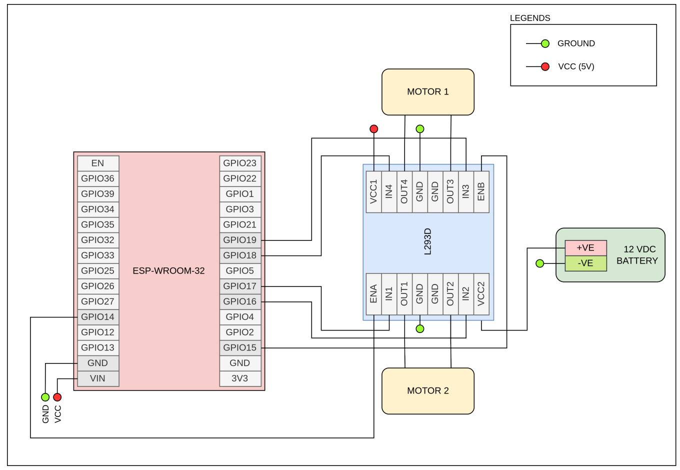

Fig. 1: Wiring Diagram for Beacon Tracking.

4 Implementation

4.1 Assets

1) UGV chassis with DC motors
2) ESP32 microcontroller with Type-B USB cable
3) L293D Motor Driver IC
4) Breadboard and Jumper Wires
5) Android phone
6) (Optional) USB 2.0/3.0 Hub

4.2 Procedure

1) Make the connections as per the wiring diagram in Figure 1.
2) Connect the ESP32 board to your Android Phone.
3) Generate the firmware by entering the following commands.

```
$ cd codes
$ pio run
```

4) Go to ArduinoDroid and select

```
Actions → Upload → Upload Precompiled
```

and choose the firmware file at

```
codes/.pio/build/firmware.hex
```

5) Now put the phone at a reasonable distance from the UGV with no obstacles in the way and then turn on the hotspot. The UGV should travel towards the phone and stop near it.

5 Results

The UGV eventually converges close to the beacon (here, the hotspot). However, if there are a lot of nearby obstacles, the UGV may not converge close to the location of the beacon. It may either get physically blocked by the beacon or the signal interference may be too high.

6 Conclusion and Future Work

In this paper, we presented a cost-effective and robust beacon tracking algorithm that uses RSSI measurements to approach the beacon at each step. Our work uses easily available hardware and software tools to implement the algorithm on an ESP32 microcontroller mounted on a UGV chassis. A further extension to this work could be to use additional sensors such as a gyroscope or an accelerometer to improve the accuracy of the UGV's position and prevent deviations from the intended path of the UGV.

References

[1] N. El-Sheimy and Y. Li, "Indoor navigation: State of the art and future trends," *Satellite Navigation*, vol. 2, no. 1, p. 7, May 2021.

[2] K. L. Narayanan, R. S. Krishnan, L. H. Son, N. T. Tung, E. G. Julie, Y. H. Robinson, R. Kumar, and V. C. Gerogiannis, "Fuzzy Guided Autonomous Nursing Robot through Wireless Beacon Network," *Multimedia Tools and Applications*, vol. 81, no. 3, pp. 3297–3325, Jan. 2022.

[3] A. Famili, A. Stavrou, H. Wang, and J.-M. Park, "iDROP: Robust Localization for Indoor Navigation of Drones With Optimized Beacon Placement," *IEEE Internet of Things Journal*, vol. 10, no. 16, pp. 14 226–14 238, Aug. 2023.

[4] M. H T, M. L, and M. Sajjad, "ROS Powered Autonomous Mobile Robot for Indoor Applications," in *2024 International Conference on Intelligent Algorithms for Computational Intelligence Systems (IACIS)*, Aug. 2024, pp. 1–7.

[5] D. A. Yukhimets, I. E. Naidanova, and N. V. Andrukhovsky, "Local Navigation System for a Robot Based on a Network of BLE Beacons," in *2024 International Russian Automation Conference (RusAutoCon)*, Sep. 2024, pp. 611–616.

[6] N. Stefas, H. Bayram, and V. Isler, "UAV Landing at an Unknown Location Marked by a Radio Beacon," in *2019 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, Nov. 2019, pp. 4409–4414.

[7] Y. Liu, E. Wang, S. Xu, Z. Wang, M. Liu, and W. Shu, "Simple Online Unmanned Aerial Vehicle Tracking with Transformer," in *2021 IEEE 20th International Conference on Trust, Security and Privacy in Computing and Communications (TrustCom)*, Oct. 2021, pp. 1235–1239.

[8] I. Masmitja, M. Martin, K. Katija, S. Gomariz, and J. Navarro, "A reinforcement learning path planning approach for range-only underwater target localization with autonomous vehicles," in *2022 IEEE 18th International Conference on Automation Science and Engineering (CASE)*, Aug. 2022, pp. 675–682.

[9] A. K. Kashyap and K. Konathalapalli, "Autonomous navigation of ROS2 based Turtlebot3 in static and dynamic environments using intelligent approach," *International Journal of Information Technology*, Mar. 2025.

[10] Sachinkumar Omprakash Dubey, "Navigation and Communication for UGV/UAV," Ph.D. dissertation, Indian Institute of Technology, Hyderabad, Jun. 2022.