CHAPTER 1
INTRODUCTION

1.1 Background

Localization remains an important topic of research to this day. It is a widely implemented technology for monitoring, mapping, tracking, and navigation purposes. One of the key research challenges is optimizing localization through methods that deliver accurate measurements, high energy efficiency, low cost, robustness, high scalability, and low computational complexity [1][2][3].

Generally, localization technology is divided into two categories, *Outdoor Positioning System* (OPS) and *Indoor Positioning System* (IPS). Outdoor Positioning Systems, such as Global Positioning System (GPS) technology, require an open environment free from obstacles. Thus, GPS technology is highly ineffective when applied to enclosed indoor spaces due to their complex environmental conditions. To address this limitation, Indoor Positioning System (IPS) technology is employed.

IPS technology can be implemented in real-world applications across various fields. For example Inventory and asset management in warehouses or logistics centers, Each rack or container can be equipped with a tag tracked precisely using Ultra-Wideband (UWB), significantly improving item retrieval and storage layout optimization. Then, Medical equipment monitoring in hospitals Large, infrequently used devices such as ventilators, wheelchairs, EKG machines, and other medical tools can be tracked to enhance search efficiency and prevent loss. Server room management: The precise positioning of server racks or modules can be automatically mapped, assisting technicians in maintenance and device monitoring. Retail stores and exhibitions, IPS can guide visitors to locate specific products or exhibit items. Key parameters for optimizing localization include accuracy, scalability, energy efficiency, cost, latency, and computational complexity. The main challenges in localization involve overcoming physical obstructions, mitigating measurement noise, minimizing signal interference, and achieving high positional accuracy while maintaining energy efficiency, cost-effectiveness, and low computational overhead [4][5]. Based on literature reviews, several studies have proposed solutions to these challenges. Some still rely on conventional localization methods, while others focus on optimizing and refining existing approaches.

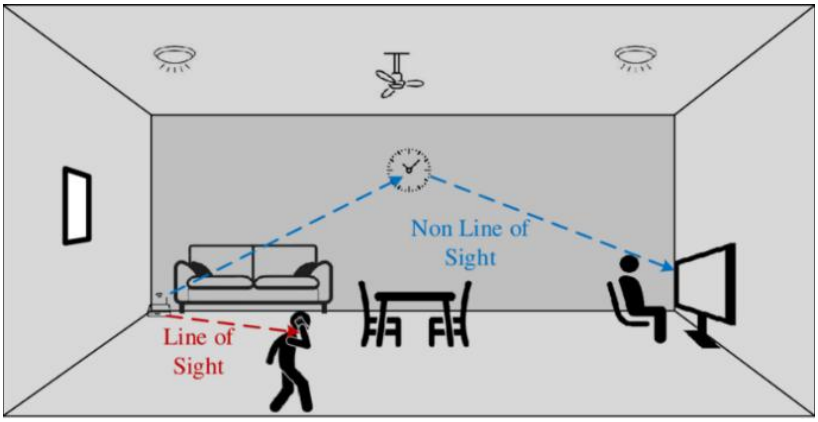

Figure 1.1 Illustration of LOS and NLOS Indoor Localization.

Figure 1.1 illustrates the Line of Sight (LOS) condition, where the communication path between the Transmitter (Tx) and Receiver (Rx) is direct and unobstructed. In contrast, the Non-Line of Sight (NLOS) condition occurs when obstacles block the Tx-Rx path, introducing signal noise due to reflections (multipath propagation). Indoor Positioning Systems (IPS) rely on several parameters to determine an object's location, with Received Signal Strength Indicator (RSSI) being one of the most commonly used. RSSI is defined as the power measured by the received signal strength circuitry, or equivalently reported as the squared magnitude of the signal. In indoor environments, signal strength often becomes unstable, degrading positioning accuracy. This instability arises primarily from obstacles (e.g., walls, furniture) obstructing the signal path between Tx and Rx a phenomenon categorized as NLOS and inherent to signal propagation challenges.

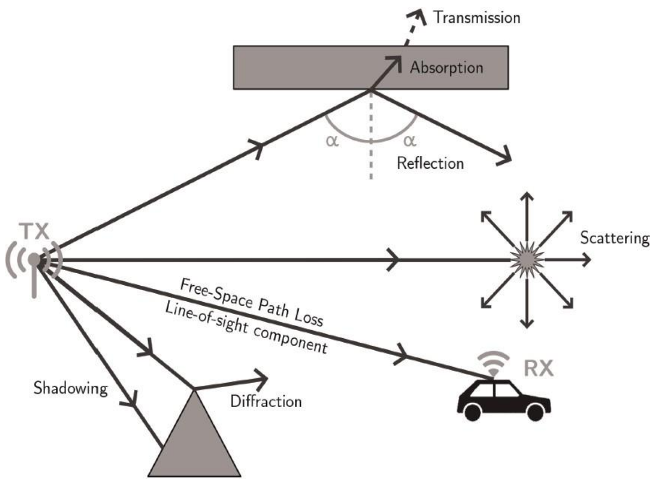

Figure 1.2 *Signal Propagation and Phenomena* [5].

Figure 1.2 demonstrates signal propagation phenomena that lead to multipath and NLOS (Non-Line of Sight) conditions. Multipath and NLOS occur when obstacles exist between the transmitter and receiver, causing signals to propagate through multiple paths. This results in unstable and fluctuating RSSI (Received Signal Strength Indicator) values even when measured at the same position. To address these issues, this study examines the use of Kalman filtering to stabilize RSSI values in indoor environments. The technology employed is Ultra-Wideband (UWB), selected for its key characteristics: wide frequency usage, high precision, interference resistance, and low power consumption making it particularly suitable for indoor positioning applications. The Kalman filter method is implemented because it can effectively reduce RSSI fluctuations while improving positioning accuracy in complex indoor environments.

Several localization methods exist to achieve accurate results with energy efficiency, cost-effectiveness, and measurement noise mitigation. One such approach is the Adaptive Kalman Filter (AKF), which dynamically adjusts filter parameters (e.g., noise adaptation or other variable parameters) to minimize measurement errors/noise [6][7]. The challenge of variable filtering against noise necessitates modifications to conventional filters, hence the development of AKF.

Previous research has utilized Kalman filters to obtain accurate localization results and address measurement noise issues. A primary source of such noise is NLOS conditions caused by obstructions during indoor positioning [8][9][10].

Therefore, this thesis proposes to study and implement an "Adaptive Kalman Filter (AKF) to Enhance Positioning Accuracy in Non-Line of Sight (NLOS) Indoor Localization Systems."

1.2 Problem Identification

The following issue have been identified in this research:

1) Complex indoor environments with obstacles can create NLOS (Non-Line-of-Sight) conditions, leading to inaccurate position estimation.
2) Standard Kalman Filter (KF) performs optimally in linear environments with constant noise. However, in dynamic and nonlinear NLOS conditions, it lacks sufficient adaptability to handle varying errors.
3) Noise variations due to NLOS are not always effectively detected, necessitating a positioning algorithm capable of adapting to received signal power (Rx power) in response to changing signal characteristics.

1.3 Objectives Research

The Objectives of this study are as follows:

1) To analyze the impact of LOS (Line-of-Sight) and NLOS (Non-Line-of-Sight) conditions on the accuracy performance of Indoor Localization Systems.
2) To implement a Standard Kalman Filter (KF) algorithm in indoor localization systems to improve positioning accuracy under both LOS and NLOS conditions.
3) To implement an Adaptive Kalman Filter (AKF) algorithm in indoor localization systems, enabling dynamic adjustment of filter parameters (e.g., Rx power).
4) To compare the performance of Adaptive Kalman Filter (AKF) and Standard Kalman Filter (KF) in terms of positioning accuracy relative to ground truth data.

1.4 Scope of Work

This study is subject to the following constraints:

1) The experimental system employs multilateration with 4 anchors and 1 tag using the ESP32 UWB Pro with Display module.
2) Performance comparison is limited to Kalman Filter variants and excludes other estimation methods (e.g., Particle Filter, Extended Kalman Filter, or AI-based approaches).
3) Distance measurement between anchors and tags utilizes the two-way ranging (TWR) method.

4) NLOS Condition with obstacle is whiteboard, in the testing room like tables, chairs, wall display, and etc doesn't include obstacle.
5) Tag displacement and positioning determination is performed manually by human operators and tag doesn't move.
6) The adaptive parameter is restricted to Rx power variations obtained from experimental data simulations.
7) Implementation *kalman filter* standar (KF) and *adaptive kalman filter* (AKF) in Non-Line of Sight (NLOS).
8) The study does not analyze obstacle materials or compositions.
9) The testing system operates in two-dimensional (2D) space only.
10) The research does not address potential outlier data in experimental results.

1.5 Hypothesis

The implementation of an Adaptive Kalman Filter (AKF) is hypothesized to improve object position estimation accuracy under Non-Line-of-Sight (NLOS) conditions in indoor localization systems compared to the Standard Kalman Filter (KF). Furthermore, Ultra-Wideband (UWB) technology is considered particularly suitable for indoor localization applications including tracking and monitoring especially in NLOS environments [11].

1.6 Research Methodology

The research methodology employed in this study consists of the following stages:

1) Literature Review

   A comprehensive examination of theoretical foundations supporting the implementation of standard Kalman Filter (KF) and Adaptive Kalman Filter (AKF) in NLOS indoor localization systems. This includes technical and regulatory aspects, with references drawn from books, research journals, papers, and technical documentation.

2) Data Collection

   Design and execution of *Indoor Localization* to collecting data distance between *anchor* and *Tag* d (m), Rx *Power* (dBm), Positioning accuracy data for both KF and AKF under NLOS conditions

   The collected data undergoes processing for subsequent analysis. Additional regulatory data regarding Ultra-Wideband (UWB) frequency usage is also compiled.

3) Technical Analysis

   Implementation of the standard Kalman Filter (KF) as a baseline and Adaptive Kalman Filter (AKF) for indoor localization under both LOS and NLOS conditions. Comparison of positioning accuracy between ground truth, KF, and AKF under various LOS/NLOS scenarios. Accuracy performance is measured using RMSE (Root Mean Square Error) and MAE (Mean Absolute Error) metrics. Quantitative comparison between KF and AKF results is conducted, accompanied by visualization of actual versus predicted coordinates through graphical representations.

4) Regulatory and Economic Analysis

   Provide an analysis regarding the regulations for the use of Ultra-Wideband (UWB) frequency and the application of the Kalman Filter in Indoor Localization, from the perspective of regulatory compliance, legal frameworks, and economic considerations.

5) Conclusion

   Synthesis of findings to address the initial research problems and validate the hypothesis. The study demonstrates that AKF enhances positioning accuracy and minimizes errors in complex NLOS environments. Consequently, AKF proves effective for dynamic parameter adaptation based on environmental noise variables.