PEOPLE'S DEMOCRATIC REPUBLIC OF ALGERIA
Ministry of Higher Education and Scientific Research
University of Mohamed El Bachir El Ibrahimi
Faculty of Science and Technology



DOCTORAL THESIS

Presented to obtain the degree of **DOCTOR**

In : Electronics

Specialty : Embedded Systems

By : Hamadi Anwar

Topic

Contribution au développement de nouvelles approches dédiées à l'assistance à la navigation indoor des personnes malvoyantes

Publicly defended, on **11/06/2025**, before a jury composed of :

Mr.	BEKKOUCHE Tewfik	Professor	at UBBA	President
Mr.	LATOUI Abdelhakim	Professor	at UBBA	Thesis Director
Mr.	DAACHI Mohamed El Hossine	Professor	at UBBA	Examinator
Mr.	AMARDJIA Noureddine	Professor	at UFAS	Examinator
Mr.	BOUGUEZEL Saad	Professor	at UFAS	Examinator

Abstract This thesis explores innovative approaches to assist visually impaired individuals in indoor navigation through the development of advanced localization and robotic systems. The research focuses on two main contributions: (1) a step-detection-controlled robotic guide dog that synchronizes with the user's walking pace and provides real-time obstacle detection, and (2) a smartphone-based indoor localization system that integrates ORB-SLAM camera with PDR inertial sensors . The robotic guide dog leverages smartphone accelerometers and ultrasonic sensors to ensure safe and adaptive navigation, while the smartphone-based system combines visual and inertial data to achieve high-precision indoor positioning. Experimental results demonstrate the effectiveness of both systems, with the robotic guide dog successfully synchronizing with user steps and avoiding obstacles, and the smartphone-based system reducing localization errors significantly compared to standalone methods. This research contributes to the field of assistive technologies by providing cost-effective, reliable, and user-friendly solutions for visually impaired individuals, enhancing their independence and mobility in indoor environments.

Résumé Cette thèse explore des approches innovantes pour aider les personnes malvoyantes à naviguer en intérieur grâce au développement de systèmes de localisation et de robots avancés. La recherche se concentre sur deux contributions principales : (1) un chien-guide robotique contrôlé par détection de pas qui se synchronise avec la vitesse de marche de l'utilisateur et fournit une détection d'obstacles en temps réel, et (2) un système de localisation intérieure basé sur smartphone qui intègre Caméra ORB-SLAM (localisation et cartographie simultanées) avec capteurs inertiels PDR . Le chien-guide robotique utilise des accéléromètres de smartphone et des capteurs ultrasoniques pour assurer une navigation sûre et adaptative, tandis que le système basé sur smartphone combine des données visuelles et inertielles pour atteindre une localisation intérieure de haute précision. Les résultats expérimentaux démontrent l'efficacité des deux systèmes, avec le chien-guide robotique réussissant à se synchroniser avec les pas de l'utilisateur et à éviter les obstacles, et le système basé sur smartphone réduisant considérablement les erreurs de localisation par rapport aux méthodes autonomes. Cette recherche contribue au domaine des technologies d'assistance en fournissant des solutions rentables, fiables et conviviales pour les personnes malvoyantes, améliorant ainsi leur indépendance et leur mobilité dans les environnements intérieurs.

Contents

Abstract i
Résume i

Contents **ii**

List of Figures **vi**

List of Tables **viii**
List of Acronyms ix
Acknowledgements & Dedication xi
Introduction 1

1 Introduction to Localization and Navigation Systems **3**
1.1 Introduction 4
1.2 From Ancient Tools to Modern Tech: The Evolution of Localization . . . 5
1.3 Historical Development 5
1.4 Fundamentals of Localization 6
1.4.1 Coordinate Systems 6
1.4.2 Reference Points and Anchors 6
1.4.3 Measurement Techniques 7
1.5 Types of Localization Systems 7
1.5.1 Outdoor Localization Systems 7
1.5.1.1 Global Navigation Satellite Systems (GNSS) 7
1.5.1.2 How GNSS Works 8
1.5.2 Indoor Localization Systems 8
1.5.3 Hybrid Localization Systems 9
1.5.3.1 Combining Multiple Technologies 9
1.6 Key Challenges in Localization and Navigation 9
1.7 Applications of Localization and Navigation Systems 9
1.7.1 Autonomous Vehicles 10
1.7.1.1 Applications of localization in autonomous vehicles . . 10
1.7.2 Robotics and Drones 11
1.7.2.1 Applications in this domain 11
1.7.3 Pedestrian Localization 12
1.7.3.1 Critical applications of pedestrian localization 12
1.8 Future Trends and Innovations 13
1.8.1 Enhanced Sensor Fusion Techniques 13

1.8.2 Artificial Intelligence and Machine Learning . . . 14
1.8.3 5G and Ultra-Wideband Technology . . . 14
1.8.4 Quantum Navigation and Timing . . . 14
1.8.5 Advances in SLAM for Unstructured Environments . . . 14
1.8.6 Edge Computing and Distributed Localization . . . 14
1.8.7 Energy-Efficient Localization Solutions . . . 15
1.8.8 Privacy-Preserving Localization Techniques . . . 15
1.9 Conclusion: . . . 15

2 State of the Art in Indoor Localization: Approaches and Technologies 17
2.1 Introduction . . . 18
2.2 Classification of Indoor Localization Approaches . . . 18
2.2.1 Types of Signals Used . . . 18
2.2.2 Active versus Passive Systems . . . 19
2.2.3 Presence of Embedded Information in Signals . . . 19
2.3 Indoor Localization Methods . . . 19
2.3.1 Time-Based Measurement Techniques . . . 20
2.3.1.1 Time-of-arrival (TOA) Technique . . . 20
2.3.1.2 Time Difference of Arrival (TDoA) Technique . . . 21
2.3.1.3 Round Trip Time (RTT) Technique . . . 21
2.3.2 Angle-Based Measurement Techniques . . . 22
2.3.2.1 Phase Difference of Arrival (PDoA) Technique . . . 22
2.3.2.2 Angle-of-arrival (AOA) Technique . . . 23
2.3.3 Channel-Based Techniques . . . 23
2.3.3.1 Received Signal Strength (RSS) . . . 23
2.3.4 Position Estimation Techniques . . . 24
2.3.4.1 Proximity Detection . . . 24
2.3.4.2 Fingerprinting . . . 25
2.3.5 Tracking Techniques . . . 26
2.3.5.1 Pedestrian Dead Reckoning . . . 26
2.3.5.2 Filters . . . 28
2.3.5.3 Simultaneous Localization and Mapping (SLAM) Algorithm . . . 28
2.4 Technologies for Indoor Localization . . . 29
2.4.1 Radio Frequency-Based Technologies . . . 29
2.4.1.1 Wireless Fidelity (Wi-Fi) -Based Indoor Positioning . . . 29
2.4.1.2 Indoor Localization Using Bluetooth . . . 30
2.4.1.3 ZigBee . . . 31
2.4.1.4 Radio Frequency Identification (RFID) Technology . . . 31
2.4.1.5 Ultrawide Band (UWB) Technology . . . 33
2.4.2 Optical Technologies . . . 33
2.4.2.1 Infrared Technology for Localization and Navigation . . . 33
2.4.2.2 Visible Light Communication for Localization and Navigation . . . 34
2.4.3 Sound-Based Technologies for Localization and Navigation . . . 35
2.4.3.1 Ultrasound Systems . . . 35

2.4.3.2 Audible Sound Technologies . . . 36
2.4.4 Inertial Sensors Technology . . . 36
2.4.4.1 Accelerometers . . . 36
2.4.4.2 Gyroscopes . . . 36
2.4.4.3 Magnetometers . . . 37
2.4.5 Vision Positioning Systems (VPS) . . . 37
2.4.6 Challenges and Limitations of Indoor Localization . . . 37
2.4.6.1 Signal Propagation and Attenuation . . . 38
2.4.6.2 Multipath Interference and Line-of-Sight Requirements 38
2.4.6.3 Synchronization Issues . . . 38
2.4.6.4 Inherent Limitations of Sensors . . . 38
2.4.7 Trends and Emerging Technologies in Indoor Localization . . . 38
2.5 Conclusion . . . 39

3 Design of a Step-Detection System for a Guide Dog Robot for the Visually Impaired 40
3.1 Introduction: . . . 41
3.2 Existing Technologies for Assisting Visually Impaired Individuals . . . 41
3.3 Advancements in Robotics for Assisting the Visually Impaired . . . 42
3.3.1 Navigation and Mobility Assistance . . . 42
3.3.2 Object Recognition and Retrieval . . . 42
3.3.3 Social Interaction and Communication . . . 42
3.3.4 Wearable Robotics and Haptic Feedback . . . 42
3.4 Guide Mobile Robots as an Alternative to Guide Dogs . . . 43
3.4.1 Types of Guide Mobile Robots . . . 43
3.4.2 Challenges in Human-Robot Interaction . . . 44
3.4.3 Speed Control and User Adaptation . . . 45
3.5 Design and Development of the Robot Guide Dog . . . 45
3.5.1 Hardware Components and Sensors . . . 45
3.5.1.1 Microcontroller and Processing Unit . . . 46
3.5.1.2 Motion and Navigation System . . . 47
3.5.1.3 Obstacle Detection and Avoidance . . . 47
3.5.1.4 Step Detection and User Synchronization . . . 47
3.5.2 Software Framework and Android Application . . . 48
3.5.2.1 Android Application Design . . . 48
3.5.2.2 Bluetooth Communication . . . 50
3.5.2.3 Real-Time Feedback and Alerts . . . 51
3.5.2.4 Step Tracking and Distance Calculation . . . 52
3.5.3 Application Testing and User Feedback . . . 52
3.5.3.1 Usability Testing . . . 52
3.5.3.2 User Feedback . . . 53
3.5.3.3 Technical Testing . . . 53
3.5.3.4 Improvements Based on Feedback . . . 53
3.6 Experimental Validation and Results . . . 53
3.6.1 Test Environment . . . 53
3.6.2 Step Synchronization Tests . . . 54

3.6.3 Obstacle Detection and Avoidance Tests . . . 55
3.6.4 Overall System Performance . . . 55
3.7 Discussion and Future Work . . . 56
3.7.1 Key Findings . . . 56
3.7.2 Limitations . . . 59
3.7.2.1 Future Work . . . 59
3.8 Conclusion: . . . 59

4 Development of an Accurate Smartphone-Based Approach for Indoor Pedestrian Localization Using ORB-SLAM and PDR Sensors 61
4.1 Introduction: . . . 62
4.2 Background and Literature Review . . . 62
4.2.1 Pedestrian Dead Reckoning (PDR) Approaches . . . 62
4.2.2 Visual SLAM for Indoor Localization . . . 63
4.2.3 Sensor Fusion for Enhanced Localization . . . 63
4.2.4 Contributions of This Work . . . 64
4.3 A smartphone-based ORB-SLAM-Inertial fusion approach . . . 64
4.3.1 ORB-SLAM Smartphone Camera Integration . . . 65
4.3.1.1 Tracking Module . . . 66
4.3.1.2 Local mapping module . . . 66
4.3.1.3 Loop Closing Module . . . 67
4.3.2 PDR Inertial Sensors Integration . . . 67
4.3.2.1 Step Detection . . . 68
4.3.2.2 Step Length Estimation . . . 69
4.3.2.3 Heading Determination . . . 69
4.3.2.4 Pedestrian Position Estimation . . . 71
4.3.3 Sensor Fusion Approach . . . 72
4.3.3.1 Prediction Step . . . 73
4.3.3.2 Update Step . . . 73
4.4 Experimental Evaluation . . . 74
4.4.1 Experimental Setup . . . 74
4.4.2 Establishing a Reference Path . . . 78
4.4.3 Methodology . . . 79
4.5 Results and Discussion . . . 79
4.6 Conclusion . . . 84
Conclusion . . . 85

Bibliography 87

List of Figures

1.1 Satellite Constellation for GPS Coverage [29]. 8
1.2 An example of vehicle lane detection scenarios using a camera sensor [38]. . 10
1.3 Warehouse automation using ground-based robots and aerial drones [40] . . . 12
1.4 (a) Laser-SLAM-enabled smart cane(b) Schematic representation of the smart cane system [46]. 13

2.1 Classification of Localization/Positioning Techniques. 20
2.2 Methods for Determining Location Using (a) ToA, (b) TDoA, and (c) RTT in Wireless Networks 22
2.3 Angle-Based Localization Methods: (a) Phase of Arrival (PoA) and (b) Angle of Arrival (AoA) [34] 23
2.4 Proximity localization technique. 25
2.5 Fingerprinting localization technique [34]. 26
2.6 The working architecture of PDR [67]. 27
2.7 The process flow of INS [34]. 27
2.8 Step and Heading System (SHS) [34]. 28
2.9 Structure of an Indoor Positioning System Using Wi-Fi and the Fingerprinting Method [67]. 30
2.10 VLC approach [34]. 35

3.1 A wheeled guide robot featuring a stereo camera, LiDAR, motorized wheels, and a tactile handle for guiding visually impaired individuals [137]. 44
3.2 A quadruped guide robot guiding a visually impaired individual by dynamically adjusting its movement based on environmental perception [138]. 44
3.3 Configuration of the proposed Robot Dog Guide System. 46
3.4 Step detection principle. 49
3.5 A screenshot of Step-Tracking Robot Guide Application. 50
3.6 Flowchart Robot Dog Guide Functioning. 51
3.7 Prototype guide dog for the visually impaired. 54
3.8 Robot Guide App Interface Obstacle Detection Test Scenarios. 57
3.9 Testing Step-Controlled Robot Guide for the Visually Impaired. 58

4.1 Architecture of the proposed navigation system. 65
4.2 Flowchart of the ORB-SLAM-based positioning algorithm utilizing a smartphone camera. 65
4.3 An example of feature matching from Path 1, as detailed in the experimental section, is presented. 66

4.4 An example of a detected loop in the laboratory is shown, where the inlier correspondences supporting the identified similarity transformation are highlighted. 67
4.5 Diagram of the PDR-Inertial positioning algorithm that leverages a smartphone's IMU. 68
4.6 Step identification through the analysis of vertical acceleration variations along the (Z-axis). 69
4.7 Estimation of the azimuth angle. 70
4.8 Building in which experiments were carried out: Faculty ofSciences and Technology. 75
4.9 Test environment of Path 1 and 2: Small Classroom. 75
4.10 Test environment of Path 3: Big Classroom. 76
4.11 Screenshot of the developed android-based navigation application. 77
4.12 Our indoor navigation system. 77
4.13 The IMU module used in our experiments to track motion and orientation. . . 78
4.14 Localization trajectory for Path 1 (Small Classroom) inComparison to the ground-truth reference Path. 81
4.15 Localization trajectory for Path 2 (Small Classroom) inComparison to the ground-truth reference Path. 81
4.16 Localization trajectory for Path 3 (Big Classroom) in comparisonTo the ground-truth reference Path. 82
4.17 Localization trajectory for Path 4 multiple loops (Big Classroom) in comparisonTo the ground-truth reference Path. 82
4.18 Localization error with respect to time and Cumulative Distribution Function (CDF) of Localization Errors, respectively: (a) and (b) for Path 1; (c) and (d) for Path 2; (e)and (f) for Path 3. 83

List of Tables

4.1 Result of experiments of the fusion approach against PDR-Inertial and ORB-SLAM approaches. 80

List of Acronyms

- GNSS - Global Navigation Satellite Systems
- GPS - Global Positioning System
- PDR - Pedestrian Dead Reckoning
- SLAM - Simultaneous Localization and Mapping
- ORB-SLAM - Oriented FAST and Rotated BRIEF SLAM
- IMU - Inertial Measurement Unit
- UWB - Ultra-Wideband
- RFID - Radio Frequency Identification
- BLE - Bluetooth Low Energy
- Wi-Fi - Wireless Fidelity
- ToA - Time of Arrival
- TDoA - Time Difference of Arrival
- RTT - Round Trip Time
- AoA - Angle of Arrival
- PDoA - Phase Difference of Arrival
- RSS - Received Signal Strength
- CSI - Channel State Information
- LQI - Link Quality Indicator
- INS - Inertial Navigation System
- SHS - Step and Heading System
- EKF - Extended Kalman Filter
- UKF - Unscented Kalman Filter

- VLC - Visible Light Communication
- IR - Infrared
- SCAN - Simultaneous Calibration and Navigation
- MEMS - Micro-Electro-Mechanical Systems
- VPS - Vision Positioning Systems
- AI - Artificial Intelligence
- ML - Machine Learning
- 5G - Fifth Generation
- V2X - Vehicle-to-Everything
- SARs - Socially Assistive Robots
- NLP - Natural Language Processing
- EMA - Exponential Moving Average
- ENU - East-North-Up
- BA - Bundle Adjustment
- ADAS - Advanced Driver-Assistance Systems
- ETAs - Electronic Travel Aids
- LiDAR - Light Detection and Ranging
- SIFT - Scale-Invariant Feature Transform
- SURF - Speeded-Up Robust Features
- ORB - Oriented FAST and Rotated BRIEF
- PS-VINS - Pedestrian SLAM-Visual Inertial Navigation System
- RESLAM - Real-Time Edge-Based SLAM
- PTAM - Parallel Tracking and Mapping
- LANDMARC - Location Identification Based on Dynamic Active RFID Calibration
- VSLAM - Visual SLAM
- LSTM - Long Short-Term Memory
- k-NN - k-Nearest Neighbors
- PF - Particle Filter
- KF - Kalman Filter
- EKF – Extended Kalman Filter

Acknowledgements & Dedication

Above all, I extend my deepest gratitude and praise to ALLAH, the Almighty, for guiding me on the right wa and granting me the strength, health, courage, and patience needed to complete this meaningful thesis.

I dedicate this modest work and my profound gratitude to my parents, my siblings, and my entire family (my wife and my son) for their unwavering encouragement and prayers, which have enabled me to achieve this modest accomplishment. I am immensely grateful for the confidence they have placed in me.

I would like to express my deepest gratitude to my advisor, Professor Abdelhakim Latoui from Bordj Bou Arreridj University , for their invaluable guidance, support, and encouragement throughout the course of this research. Their expertise, patience, and insightful feedback have been instrumental in shaping this thesis.

I extend my sincere appreciation to the members of my thesis committee, Professor M.E. Daachi , Professor AMARDJIA Noureddine, Professor BOUGUEZEL Saad, Professor BEKKOUCHE Tewfik, for their valuable time, constructive criticism, and thoughtful suggestions that greatly improved the quality of this work.

I am truly honored to have had the opportunity to be evaluated by such experts.

Finally, I am deeply thankful to my friends and loved ones for their constant support and understanding during this challenging yet fulfilling journey. Their encouragement has helped me stay focused and determined.

This thesis is dedicated to everyone who has supported me in this academic pursuit. I am truly grateful for all the help and kindness I have received.

May God's blessings and peace be upon Mohammad and his family and all companions.

Introduction

Using a smartphone for indoor navigation can be a valuable and empowering tool, particularly for visually impaired individuals, as it promotes independence and safe mobility. Unlike outdoor environments, where the GPS ensures reliable positioning, indoor navigation presents significant challenges due to signal attenuation, reflection, and occlusion, rendering GPS ineffective in such settings [1]. Consequently, achieving high-precision indoor localization without relying on GPS has become a critical research focus.

One widely adopted approach to indoor positioning is wireless localization technology [2], which utilizes dedicated transmitters such as Bluetooth beacons [3], Wi-Fi routers [4], and UWB transmitters. Despite these systems offer effective solutions, they require substantial infrastructure investment and ongoing maintenance, limiting their scalability and widespread adoption.

In recent years, MEMS-based inertial sensors, including accelerometers and gyroscopes, have gained prominence due to their compact size, lightweight design, and independence from external signals [5, 6]. Modern smartphones are equipped with these sensors, which makes them particularly effective for indoor navigation tasks, especially in assisting users with visual impairments [7]. However, MEMS-based positioning systems rely on PDR, which accumulates errors over time due to sensor drift, leading to degraded long-term accuracy.

To address these limitations, vision-based localization methods, such as SLAM, have emerged as promising alternatives [8]. SLAM systems use smartphone cameras to determine the user's position relative to their surroundings while simultaneously creating a map of the environment. Despite their potential, SLAM-based methods are highly sensitive to environmental changes, such as moving objects and variations in lighting, which can compromise accuracy [9].

Given the complementary strengths and weaknesses of MEMS-based inertial systems and SLAM, integrating these technologies into a unified framework presents a promising solution for improving indoor localization accuracy. Previous research has explored PDR-SLAM fusion [10–13].However, achieving robust and reliable indoor navigation for visually impaired individuals using only low-cost smartphone sensors remains an open challenge.

Since our research is tailored to assist visually impaired individuals using smartphone devices, in this work, two novel methods are proposed to offer a low-cost alternative for indoor pedestrian localization.

A robotic guide dog system that leverages smartphone accelerometers for step detection, enabling synchronization between the user's walking pace and the robot's movement. Integrated with ultrasonic sensors for obstacle detection and Bluetooth communication for

real-time feedback, this system provides a cost-effective and adaptive alternative to traditional guide dogs [14].

A smartphone-based indoor localization system that combines ORB-SLAM [15], a visual mapping technique, with PDR inertial sensors to achieve high-precision indoor positioning by utilizing the smartphone's camera and IMU. By fusing visual and inertial data, this system effectively mitigates the challenges of GPS-denied environments [16].

This research is driven by the growing demand for accessible and effective assistive technologies. By integrating robotics, sensor technology, and smartphone-based solutions, this research seeks to deliver effective and adaptable solutions that assist visually impaired users in navigating indoor areas with enhanced autonomy and assurance .

This manuscript is organized into four main chapters, in addition to an introduction and a conclusion:

Chapter 1 provides an overview of localization and navigation systems, covering their evolution, fundamental concepts, and classification into indoor, outdoor, and hybrid localization methods. The chapter also discusses the key challenges associated with indoor positioning and highlights the applications of these technologies.

Chapter 2 presents a comprehensive state-of-the-art review of existing indoor localization approaches. It examines different localization techniques, including radio frequency (RF)-based, vision-based, and inertial-based methods, as well as hybrid techniques that integrate multiple sensing modalities. The advantages and limitations of these approaches are analyzed to contextualize the research problem.

Chapter 3 introduces the first major contribution of this thesis: the step-detection-controlled robotic guide dog. It details the system's hardware and software components, including its real-time step synchronization, obstacle detection, and feedback mechanisms. Experimental evaluations and user studies are presented to assess its effectiveness for visually impaired users.

Chapter 4 describes the second contribution: a smartphone-based ORB-SLAM and PDR fusion approach for indoor localization. The system architecture, sensor fusion techniques, and experimental evaluations are detailed. The chapter presents performance comparisons against existing methods to demonstrate the proposed approach's accuracy and reliability.

The conclusion summarizes the key findings, discusses limitations, and outlines future research directions for enhancing smartphone-based indoor navigation systems.

By structuring the thesis in this manner, Our objective is to conduct a thorough and structured study focused on designing localization systems that are both affordable and highly accurate for visually impaired users.

Chapter 1

Introduction to Localization and Navigation Systems

1.1 Introduction

Localization and navigation systems are vital technologies that determine the position of an object or individual and guide them through an environment. Localization involves identifying an entity's location within a defined coordinate system, while navigation directs that entity from one point to another, often through complex, unfamiliar, or dynamic surroundings. These systems are foundational to various technologies, including autonomous vehicles, robotics, smartphone navigation, and assistive technologies for visually impaired individuals.

Moreover, the applications of localization and navigation systems span various fields, including:

- **Transportation:** These systems are critical for autonomous vehicles and ADAS , which depend on precise localization to navigate roads, avoid obstacles, and enhance safety [17]. They also improve public transportation by optimizing route planning and enabling real-time vehicle tracking, ensuring more efficient operations [18] .
- **Industrial Assistance and Automation:** In factories and warehouses, localization systems enhance workers' and machinery's safety and precision. Autonomous robots and vehicles rely on these systems to navigate complex environments, minimize errors in material handling and repetitive tasks, and ultimately boost productivity [19].
- **Military and Defense:** In military operations, localization and navigation technologies enhance situational awareness in challenging and hazardous environments. They are critical for guiding unscrewed vehicles on the battlefield and enabling efficient troop coordination, playing an essential role in modern defense strategies [20] .
- **Daily Living Assistance:** For elderly individuals and those with visual impairments, navigation aids integrated into assistive devices or home environments enable safer and more independent movement in indoor and outdoor spaces [21] . These systems help users navigate daily tasks, avoid obstacles, and confidently move in challenging environments.

In addition, the importance of localization and navigation systems lies in their ability to deliver real-time spatial awareness and precise movement control. Whether facilitating the safe arrival of autonomous vehicles, enabling indoor navigation in GPS-denied areas like shopping malls or underground facilities, or supporting search and rescue missions in dangerous conditions, these systems enhance safety, efficiency, and intelligent interaction with the world [22].

This chapter aims to provide an overview of localization and navigation systems, covering their evolution and fundamental concepts, while discussing the classification of localization technologies, including outdoor, indoor, and hybrid systems. It highlights key challenges in indoor localization, such as sensor drift, environmental variations, and real-time processing constraints. Additionally, it establishes a foundation for the proposed assistive navigation solutions discussed in this thesis by emphasizing the need for integrating

multiple sensing modalities to achieve accurate, reliable, and scalable indoor navigation solutions for visually impaired individuals.

1.2 From Ancient Tools to Modern Tech: The Evolution of Localization

Localization can be defined as the process of identifying and tracking the location of people, objects, or devices within a defined space. This concept has been fundamental to humanity since ancient times when early societies developed methods and tools for navigation and positioning. Since time immemorial, humans have employed many instruments, including maps, compasses, astrolabes, and sextants, to ascertain their location and ensure effective navigation, whether on land, sea, or sky [23] .

In today's world, precise localization is more important than ever. It is crucial in many sectors, improving safety, operational efficiency, and management. For instance, knowing where soldiers are in military maneuvers is vital to ensure efficient teamwork and safety [24]. In the business world, monitoring the movement and location of products and shipments worldwide is essential for ensuring they are delivered on time and that logistical operations run smoothly [25]. In the medical field, swiftly identifying the whereabouts of patients or healthcare staff is critical during emergencies. Moreover, emergency response teams such as ambulance services, fire departments, and police forces depend on accurate location information to quickly arrive at the scene of an incident and provide assistance [24].

Various technologies and systems have been developed for real-time and accurate position tracking to meet the growing needs of modern society. These technologies include GPS, RFID, Wi-Fi-based indoor localization, and satellite systems [25]. Localization enables location tracking and supports remote control and guidance, which is essential in various industries. These systems ensure efficient resource utilization, risk mitigation, and effective operations by providing precise location data [20].

1.3 Historical Development

Technological advancements over the centuries have shaped the evolution of localization and navigation systems [26]. In the early days, navigation relied on natural landmarks and celestial bodies like the stars and the sun, guiding humans through land and sea. A significant breakthrough came with the development of the compass in ancient China, revolutionizing navigation by enabling orientation in any weather condition and laying the foundation for more precise navigation.

Technological advances in the 20th century led to radio-based navigation systems and the GPS, marking a significant milestone in outdoor localization [25]. Initially developed by the U.S. Department of Defense, GPS revolutionized outdoor navigation by providing high-accuracy real-time positioning. It was rapidly adopted across various industries, from aviation and maritime navigation to personal navigation tools like smartphones [27] .

As GPS solved many challenges for outdoor navigation , attention shifted toward indoor environments where GPS signals could not penetrate. This prompted research into

alternative methods, such as Wi-Fi-based positioning, Bluetooth beacons, infrared sensors, and magnetic field-based approaches . Alongside these developments, advancements in sensors like accelerometers and gyroscopes enabled the emergence of PDR and INS, which are viable options for continuous tracking. Today, hybrid systems combining multiple technologies are being developed to ensure accurate localization in outdoor and indoor environments [28] , paving the way for applications like autonomous robotics, augmented reality, and intelligent transportation systems.

The historical evolution of localization and navigation systems underscores their growing importance across various industries and applications. As these systems continue to evolve, they are becoming increasingly robust, accurate, and integrated into our everyday lives.

1.4 Fundamentals of Localization

Localization refers to the process of determining the position of an object or person in a given space. It is a critical component of navigation systems and is used in a wide range of applications, from consumer devices like smartphones to industrial systems like autonomous robots. The fundamentals of localization can be broken down into the following key areas.

1.4.1 Coordinate Systems

Coordinate systems form the backbone of localization, providing a structured framework for defining positions in space. These systems can be broadly categorized into global and local coordinate systems.

- **Global Coordinate Systems:** These systems, such as the GCS , use latitude and longitude to specify locations on Earth's surface [29] .The GCS is widely used in GPS and other satellite-based navigation systems, offering a universal reference for positioning.
- **Local Coordinate Systems:** In contrast, local coordinate systems, such as Cartesian coordinates, are used for smaller, defined areas like indoor environments [30] .These systems employ a grid-based approach, with axes representing distances from a fixed origin point. Cartesian coordinates are essential for high-precision applications, such as robotic navigation and indoor tracking [22] .

Each system allows for a structured and mathematical approach to determining location, making it possible to efficiently compute distances, angles, and movements. Choosing the appropriate coordinate system depends on the specific application and environment, such as whether the localization is in two-dimensional (e.g., flat indoor maps) or three-dimensional (e.g., aerial drones) spaces.

1.4.2 Reference Points and Anchors

Localization systems rely on reference points or anchors to determine position. These can be:

1. **Satellites:** In GNSS systems, satellites act as reference points for outdoor localization.
2. **Beacons or Access Points:** In indoor systems, Wi-Fi access points, Bluetooth beacons, or UWB anchors serve as reference points.
3. **Landmarks:** Physical objects or features (e.g., walls, doors) can also act as reference points in some systems [31].

1.4.3 Measurement Techniques

Measurement techniques are the core methods used by localization systems to estimate position. These techniques include Time-Based Methods (e.g., ToF, TDoA), Signal Strength-Based Methods (e.g., RSSI), Angle-Based Methods (e.g., AoA), and Proximity-Based Methods (e.g., RFID, BLE) and so on. Each technique has its strengths and limitations, depending on the environment and application. In the next chapter, we will explore these methods in detail, discussing their principles, use cases, and challenges [32].

1.5 Types of Localization Systems

Localization systems can be broadly categorized into three types based on their operational environment and the technologies they employ: Outdoor Localization Systems, Indoor Localization Systems, and Hybrid Localization Systems. Each type has its unique strengths, limitations, and applications.

1.5.1 Outdoor Localization Systems

Outdoor localization systems are designed to determine the position of objects or individuals in open environments, typically using satellite-based technologies. The most prominent example is the (GNSS).

1.5.1.1 Global Navigation Satellite Systems (GNSS)

GNSS refers to a constellation of satellites that provide geolocation and time information to GNSS receivers anywhere on or near the Earth's surface. The most widely used GNSS systems include:

1. GPS : Operated by the United States, GPS is the most well-known and widely used satellite navigation system. Figure 1.1 below illustrates the constellation of satellites that comprise (GPS) [29].
2. GLONASS : Operated by Russia, GLONASS provides global coverage and is often used in conjunction with GPS for improved accuracy.
3. Galileo: Developed by the European Union, Galileo offers high-precision positioning and is designed for civilian use.

1.5.1.2 How GNSS Works

To determine position, GNSS receivers rely on triangulation of signals emitted by multiple satellites, with each signal carrying the satellite's coordinates and the timestamp of transmission.

The receiver measures the time delay of the signals to determine the distance to each satellite. By combining data from at least four satellites, the receiver can compute its precise location (latitude, longitude, and altitude).

Despite these advances, GNSS remains primarily effective for outdoor positioning, and alternatives like Wi-Fi positioning systems, Bluetooth beacons, and UWB systems are typically used indoors where GNSS signals are weak or unavailable.

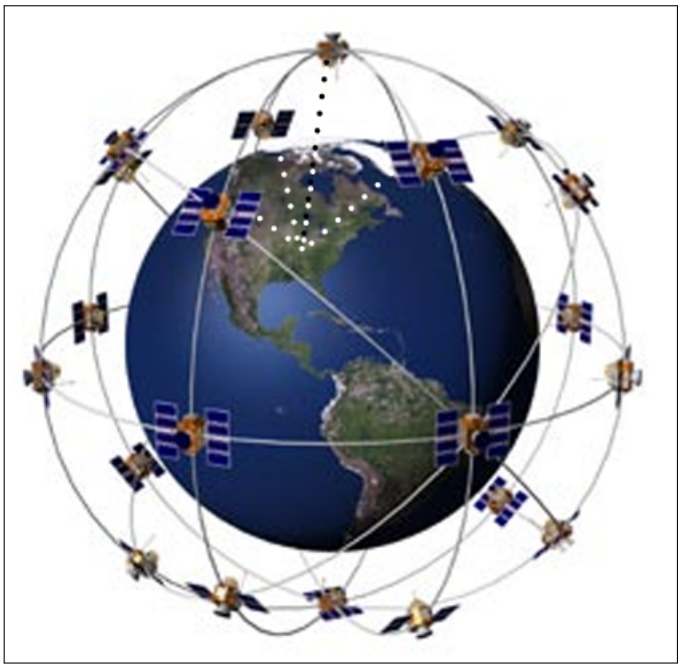


Figure 1.1: Satellite Constellation for GPS Coverage [29].

1.5.2 Indoor Localization Systems

Indoor localization systems are designed to operate in environments where GNSS signals are unavailable or unreliable, such as inside buildings, airports, or shopping malls. These systems rely on alternative technologies to provide accurate positioning.

There are many technologies used in indoor localization. For instance, Wi-Fi uses signal strength RSSI from access points for cost-effective positioning but is prone to interference. BLE employs energy-efficient beacons for proximity-based localization, making it ideal for small-scale deployments. UWB achieves centimeter-level precision by measuring signal travel time, which makes it suitable for high-accuracy applications like asset tracking . RFID enables short-range localization and is commonly used in inventory management and access control systems. Each technology offers distinct advantages depending on the use case and environment [31].

1.5.3 Hybrid Localization Systems

Hybrid localization systems combine multiple technologies to overcome the limitations of individual systems and provide seamless positioning across diverse environments. These systems integrate data from GNSS, indoor technologies, and other sensors to deliver robust and accurate localization.

1.5.3.1 Combining Multiple Technologies

- **GPS + Wi-Fi + Dead Reckoning:** In urban environments, GPS can provide outdoor positioning, while Wi-Fi and Dead Reckoning take over indoors. Dead Reckoning uses inertial sensors (e.g., accelerometers, gyroscopes) to estimate movement when external signals are unavailable.
- **UWB + BLE:** UWB provides high-precision localization, while BLE offers energy-efficient proximity detection. This combination is useful in applications like smart homes or industrial automation.
- **GNSS + LiDAR:** In autonomous vehicles, GNSS provides global positioning, while LiDAR offers high-resolution mapping of the surrounding environment [33].

1.6 Key Challenges in Localization and Navigation

Localization and navigation systems face numerous challenges that impact their accuracy, efficiency, and widespread adoption. One of the primary difficulties is achieving high precision across diverse environments, as signal interference, multipath effects, and sensor noise can significantly degrade performance. Seamless transitions between indoor and outdoor spaces remain a persistent issue since different positioning technologies are required for each setting. Power consumption is another critical concern, particularly for battery-operated devices, where continuous signal transmission and processing quickly drain energy. Scalability and infrastructure costs also pose significant barriers, as deploying large-scale localization systems demands substantial investment in hardware and maintenance. Additionally, privacy and security concerns arise from the collection and processing of sensitive location data, necessitating robust protection measures to prevent unauthorized access [34]. The reliability of these systems is further challenged by environmental variability and dynamic conditions, which can introduce inconsistencies in positioning accuracy. Lastly, the lack of standardization across different localization technologies hinders interoperability, making integration and widespread adoption more complex. Addressing these challenges is crucial to enhancing the performance, reliability, and accessibility of localization and navigation systems across various applications [33] .

1.7 Applications of Localization and Navigation Systems

Localization and navigation systems are essential across various industries, supporting numerous applications that require precise positioning and movement in complex and dynamic environments. Key application areas include Autonomous Vehicles, Robotics,

Drones, and Pedestrian Localization, leveraging advanced technologies to enhance safety, efficiency, and user experience.

1.7.1 Autonomous Vehicles

AVs rely heavily on advanced localization and navigation systems to operate safely and efficiently. These systems combine multiple sensors, such as GPS, LiDAR, radar, cameras, and IMUs, to navigate roads, detect obstacles, and follow predefined routes [35]. The fusion of these sensors allows AVs to maintain an accurate sense of their surroundings and position, even in environments where GPS signals are weak or unavailable, such as urban canyons or tunnels [36].

1.7.1.1 Applications of localization in autonomous vehicles

- Lane detection: Using cameras and LiDAR, AVs can identify lane markings to stay within the lane, adjust speed, and avoid lane departure.
- Obstacle avoidance: AVs use radar and vision sensors to detect nearby obstacles, predict their movements, and navigate around them.
- High-definition mapping: Localization systems in AVs enable continuous updating of high-definition (HD) maps, which AVs use to navigate specific road features, such as sharp turns, traffic signs, and pedestrian crossings.
- Navigation in complex environments: In urban areas, AVs use sensor fusion to maintain accuracy despite GPS interference from tall buildings, which is essential for reliable route planning and safe navigation in dense city centers [37].

Figure 1.2 illustrates detected lane markings highlighted in yellow and blue, aiding the autonomous vehicle in lane-keeping. Additionally, an obstacle (a car) is detected and enclosed within a red bounding box, showcasing the system's ability to identify surrounding objects for safe navigation.

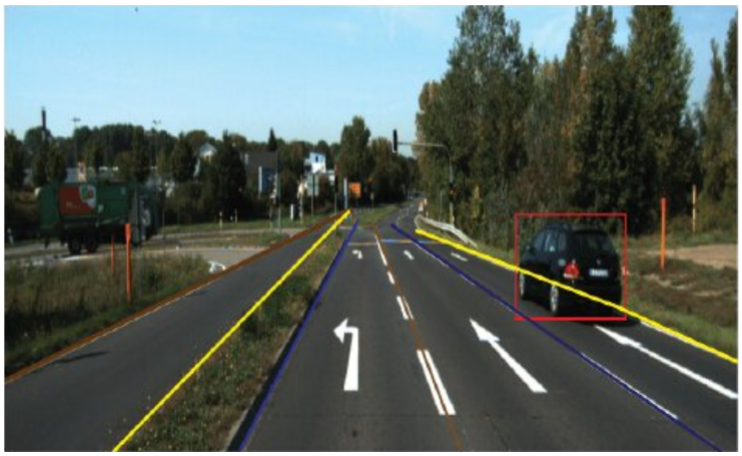


Figure 1.2: An example of vehicle lane detection scenarios using a camera sensor [38].

Advances in autonomous vehicle localization focus on reducing sensor dependency through techniques like visual odometry and map-based localization. These techniques allow AVs to utilize onboard vision-based data and environmental features rather than relying solely on GPS [22] . Machine learning models are also becoming integral, enabling AVs to continuously learn and adapt to new environments by analyzing vast amounts of data gathered during navigation.

1.7.2 Robotics and Drones

Robotics and drones depend heavily on localization and navigation systems to perform tasks ranging from simple navigation to complex, autonomous missions. Ground-based robots and aerial drones utilize various technologies for localization, including GPS, IMUs, vision-based odometry, and UWB systems. These systems enable robots and drones to conduct warehouse automation, delivery services, and industrial inspections [39].

1.7.2.1 Applications in this domain

- Warehouse automation: Mobile robots in warehouses rely on indoor positioning systems, such as LiDAR-based-SLAM , Wi-Fi positioning, or UWB systems, to locate items, transport goods, and navigate aisles. These robots increase operational efficiency and reduce labor costs by integrating mapping and localization [40].

Figure 1.3 illustrates an example of warehouse automation using ground-based robots and aerial drones. The robots navigate through the aisles to transport goods, while the drone autonomously delivers a package, demonstrating the integration of robotics in logistics management.

- Search and rescue: Drones equipped with GPS, thermal cameras, and SLAM algorithms are employed in disaster zones for search and rescue operations, enabling responders to cover large areas quickly and locate individuals in hard-to-reach areas [41].

- Inspection and maintenance: Drones are deployed for infrastructure inspections in industries like energy and construction. They use GPS, computer vision, and LiDAR to identify structural issues and improve maintenance accuracy. Drones can inspect pipelines, power lines, or construction sites, reducing the need for manual, labor-intensive inspections [42] .

- Precision agriculture: Agricultural drones employ GPS and sensors to map fields, monitor crop health, and plan precise actions such as pesticide application or irrigation adjustments, improving resource efficiency and maximizing crop yield [43].

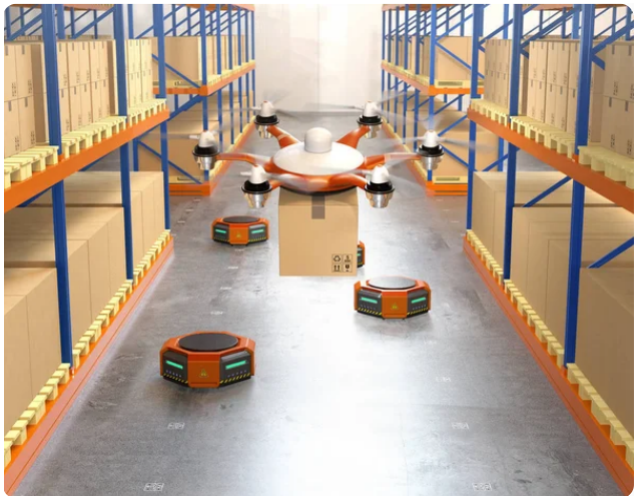


Figure 1.3: Warehouse automation using ground-based robots and aerial drones [40] .

Multi-sensor fusion is commonly employed in robotics and drones to address localization challenges in dynamic and cluttered environments. Ground-based robots often combine vision sensors with IMUs to navigate unstructured environments. In aerial applications, drones rely on visual odometry and sensor fusion techniques to maintain stability and accurate positioning, even when GPS signals are weak or disrupted, such as in forested areas or near buildings [44].

1.7.3 Pedestrian Localization

Pedestrian localization is essential for various applications that enhance safety, mobility, and user experience, particularly for vulnerable populations such as visually impaired individuals. This technology combines inertial sensors, cameras, and Wi-Fi or Bluetooth-based localization systems to provide real-time navigation instructions and alerts about obstacles.

1.7.3.1 Critical applications of pedestrian localization

- Mobility assistance for visually impaired individuals: Smart canes and wearable devices leverage pedestrian localization to guide users safely through complex environments, offering haptic and audio feedback about nearby obstacles [45]. A study [46] introduced an advanced smart cane incorporating laser SLAM technology. This system integrates a 2D LiDAR, a monocular camera, an IMU, and a GPS module, all mounted on the cane, as illustrated in Figure 1.4.

- Behavioral tracking and analysis in retail: Retail environments use pedestrian localization systems to track customer movements, enabling businesses to optimize layouts and improve customer experiences [24].

- Smart buildings: Localization technologies enhance operational efficiency in intelligent buildings by optimizing space usage and ensuring safety during emergencies [47].

- Sports and health tracking: Pedestrian localization is critical in fitness applications for tracking activities like walking or running, providing valuable insights for improving health outcomes [48] .
- Urban surveillance and security: Pedestrian localization systems improve public safety by monitoring movements and alerting authorities to suspicious activities in urban [49].



Figure 1.4: (a) Laser-SLAM-enabled smart cane(b) Schematic representation of the smart cane system [46].

1.8 Future Trends and Innovations

Localization and navigation technologies are rapidly evolving, driven by advancements in machine learning, sensor fusion, and communication networks. Future trends focus on enhancing accuracy, reliability, and adaptability, especially in complex and dynamic environments. Key innovations are transforming industries such as autonomous vehicles, robotics, healthcare, and smart cities, emphasizing the creation of more efficient, safe, and intelligent systems.

1.8.1 Enhanced Sensor Fusion Techniques

Future localization systems will continue incorporating advanced sensor fusion techniques, combining data from GPS, LiDAR, radar, and ultrasonic sensors to provide highly accurate and reliable positioning. This multi-modal approach aims to overcome the limitations of individual sensors, particularly in GPS-denied environments such as urban canyons, dense forests, and underground facilities. Sensor fusion algorithms, like Kalman and Particle Filters, are essential for real-time error correction, enabling systems to maintain accuracy under challenging conditions [20] .

1.8.2 Artificial Intelligence and Machine Learning

AI and machine learning are revolutionizing localization systems by enabling them to learn from vast datasets, adapt to environmental changes, and make autonomous decisions. Deep learning algorithms allow localization systems to recognize patterns and perform complex tasks such as semantic mapping, where an environment is mapped with rich contextual data. For autonomous vehicles, machine learning aids in real-time decision-making, allowing vehicles to navigate unpredictable environments safely [45].

1.8.3 5G and Ultra-Wideband Technology

The rollout of 5G networks and the adoption of UWB technology are expected to enhance real-time localization and data transfer capabilities significantly. 5G's low latency and high bandwidth enable connected devices to communicate and share positioning data almost instantaneously, critical for autonomous driving applications like vehicle-to-everything (V2X) communication. UWB offers highly accurate indoor positioning, making it ideal for hospitals, factories, and warehouses where precise localization is crucial [28] .

1.8.4 Quantum Navigation and Timing

Quantum technology presents a promising future for localization, particularly in GPS-denied environments. Quantum navigation systems utilize quantum sensors to provide highly accurate positioning without relying on external signals, making them invaluable in locations where traditional navigation technologies are ineffective, such as deep space, underwater, or dense urban areas. Although still in the research stage, quantum localization may soon support applications in defense, aviation, and emergency response [25].

1.8.5 Advances in SLAM for Unstructured Environments

SLAM technology is evolving to address localization challenges in unstructured and dynamic environments, such as forests or disaster areas. Future SLAM algorithms are expected to incorporate deep learning for enhanced feature extraction, enabling autonomous systems to navigate and map unknown terrains in real-time. This is particularly useful for search and rescue operations and environmental monitoring, where robots and drones must adapt to ever-changing surroundings [41].

1.8.6 Edge Computing and Distributed Localization

Edge computing, which processes data close to the source rather than relying on cloud-based servers, is gaining traction in localization. By enabling real-time data processing on devices, edge computing reduces latency, making it ideal for time-sensitive applications like autonomous driving and industrial automation. Distributed localization systems leverage edge computing to facilitate collaborative navigation, where multiple devices share positioning data to improve overall accuracy, enhancing fleet management and drone swarms [48] .

1.8.7 Energy-Efficient Localization Solutions

As localization systems become ubiquitous, energy efficiency is a growing priority. Future systems will incorporate energy-saving algorithms, low-power sensors, and renewable energy sources such as solar panels to support extended operations in resource-limited environments. LPWANs and wake-up radios are also being explored to support applications like wildlife tracking and remote monitoring, where battery life is critical [43] .

1.8.8 Privacy-Preserving Localization Techniques

Privacy concerns are more pressing than ever with the increasing use of localization data. Innovations in cryptographic methods, such as homomorphic encryption and secure multi-party computation, are enabling precise localization without compromising user privacy. These technologies are especially relevant in healthcare and personal mobility applications, where sensitive location data must be protected from unauthorized access [50].

1.9 Conclusion:

Localization and navigation systems are essential technologies that determine the position of objects or individuals and guide them through complex environments. These systems play a vital role in applications such as autonomous vehicles, robotics, and assistive technologies for visually impaired individuals. This chapter explored the evolution of localization, from ancient tools like compasses to modern systems such as GPS and indoor positioning technologies, emphasizing the importance of precise spatial awareness.

The fundamentals of localization, including coordinate systems, reference points, and measurement techniques, were examined, alongside the classification of systems into outdoor, indoor, and hybrid categories. While outdoor systems, such as GNSS, perform well in open environments, indoor systems rely on technologies like Wi-Fi and inertial sensors to mitigate challenges like signal attenuation and multipath effects.

Addressing key challenges such as sensor drift, environmental variability, and seamless indoor-outdoor transitions has led to the development of hybrid systems that integrate multiple technologies for more robust and accurate positioning. These advancements have applications across diverse domains, including autonomous vehicles, industrial automation, military operations, and daily living assistance, all contributing to improved safety, efficiency, and independence.

Future trends focus on enhancing accuracy and adaptability through advancements in sensor fusion, artificial intelligence, and emerging technologies like 5G and UWB. These innovations promise to further strengthen localization systems, making them smarter and more efficient.

In summary, localization and navigation technologies continue to evolve, addressing challenges while leveraging new advancements to improve mobility, safety, and quality of life.The next chapters will delve deeper into the state-of-the-art indoor localization methods, followed by the development and implementation of two innovative solutions: a step-detection-controlled robotic guide dog and a smartphone-based ORB-SLAM and PDR fusion system. These contributions aim to enhance mobility and independence for

visually impaired users by offering precise and reliable navigation assistance in indoor environments.

Chapter 2

State of the Art in Indoor Localization: Approaches and Technologies

2.1 Introduction

The term indoor positioning describes the use of specialized technologies to estimate the location of people, devices, or objects within indoor environments. Unlike GPS, which is ineffective indoors due to signal attenuation and interference from walls and other obstacles, IPS leverage various technologies such as radio frequency signals (Wi-Fi, Bluetooth, ZigBee, UWB, and RFID), optical signals (IR, VLC), sound waves (ultrasound, audible sound), and inertial sensors. These technologies provide accurate and reliable location information tailored for indoor environments.

The significance of indoor localization spans multiple domains, including navigation for visually impaired individuals, asset tracking in warehouses, smart building automation, personalized shopping experiences, and emergency response. However, implementing an effective IPS comes with significant challenges. Signal propagation can be affected by obstacles, leading to attenuation and multipath interference. Inertial sensors suffer from cumulative drift errors over time, while vision-based systems are susceptible to lighting variations, motion blur, and occlusions. These challenges necessitate the development of robust solutions that balance accuracy, reliability, and scalability across dynamic indoor environments.

To address these issues, various indoor localization techniques have been developed. These include time-based methods (ToA , TDoA, and RTT), angle-based methods (AoA and PDoA), channel-based approaches (RSS), and position estimation techniques (Proximity Detection, Fingerprinting). Advanced tracking methods such as PDR, Kalman Filters, and SLAM further enhance the accuracy and usability of indoor positioning systems.

This chapter provides a comprehensive overview of the state-of-the-art indoor localization technologies, methods, and challenges. It classifies different approaches based on signal type, active versus passive systems, and the presence of embedded information. Furthermore, emerging trends such as hybrid localization methods, artificial intelligence-driven fingerprinting, and the integration of IMUs with SLAM are discussed to highlight the future directions of indoor positioning research. Since this study focuses on pedestrian navigation and localization using smartphones, all discussions in this chapter are specifically attributed to smartphone-based systems.

2.2 Classification of Indoor Localization Approaches

Classifying indoor localization approaches is essential to understanding the diversity of methods and technologies available. This classification helps highlight the strengths, limitations, and applications of different systems. The main criteria for classification are the types of signals used, the distinction between active and passive systems, and the presence of embedded information in the signals.

2.2.1 Types of Signals Used

- RF: Widely used signals in Wi-Fi, Bluetooth, ZigBee, and RFID technologies. RF signals provide long-range coverage and adaptability for indoor environments, making them a dominant choice in many IPS solutions [51].

- Light: IR and visible light are used for positioning, especially in systems like VLC. Light-based systems offer high accuracy but often require line-of-sight conditions.
- Sound: Both audible and ultrasonic sound waves are used for localization. Sound travels more slowly than electromagnetic waves, enabling precise time-of-flight measurements, which are common in ultrasonic systems.

2.2.2 Active versus Passive Systems

Indoor localization systems can also be categorized as active or passive based on how the signals are generated and processed:

- Active Systems: In active configurations, the mobile device generates the signal, and the infrastructure detects it. Examples include RFID systems where tags emit signals picked up by readers. Active systems often provide higher precision but can raise privacy concerns since location data is processed externally.
- Passive Systems: In passive configurations, the mobile device receives signals emitted by the infrastructure, such as Wi-Fi or Bluetooth beacons. These systems prioritize privacy since location processing is done on the user's device. They also reduce power consumption for mobile devices but may require a more extensive infrastructure [52].

2.2.3 Presence of Embedded Information in Signals

Signals used in IPS can be classified based on whether they contain embedded information:

- With Embedded Information: Signals like Wi-Fi or VLC often encode data patterns or identifiers, enabling precise positioning. For instance, in VLC, encoded light patterns from LED bulbs help identify the user's location.
- Without Embedded Information: Some systems rely on natural or ambient signals without encoded data. For example, magnetic field-based systems or passive sound-based methods use environmental variations as unique "fingerprints" for localization [52].

2.3 Indoor Localization Methods

Indoor localization methods combine data collection, signal measurement, and algorithms to estimate the location of objects or individuals. In this section, we present a detailed overview of the key techniques and methodologies used for localization and positioning, categorized based on the measurement principles (e.g., time-based, phased and angle-based, channel-based), the estimation approaches (e.g., proximity detection, fingerprinting), and advanced tracking methods (e.g., motion-based techniques, sensor fusion filters, SLAM). These techniques are further organized to highlight their unique roles in enhancing accuracy and reliability. A comprehensive classification is illustrated in Figure2.1 .

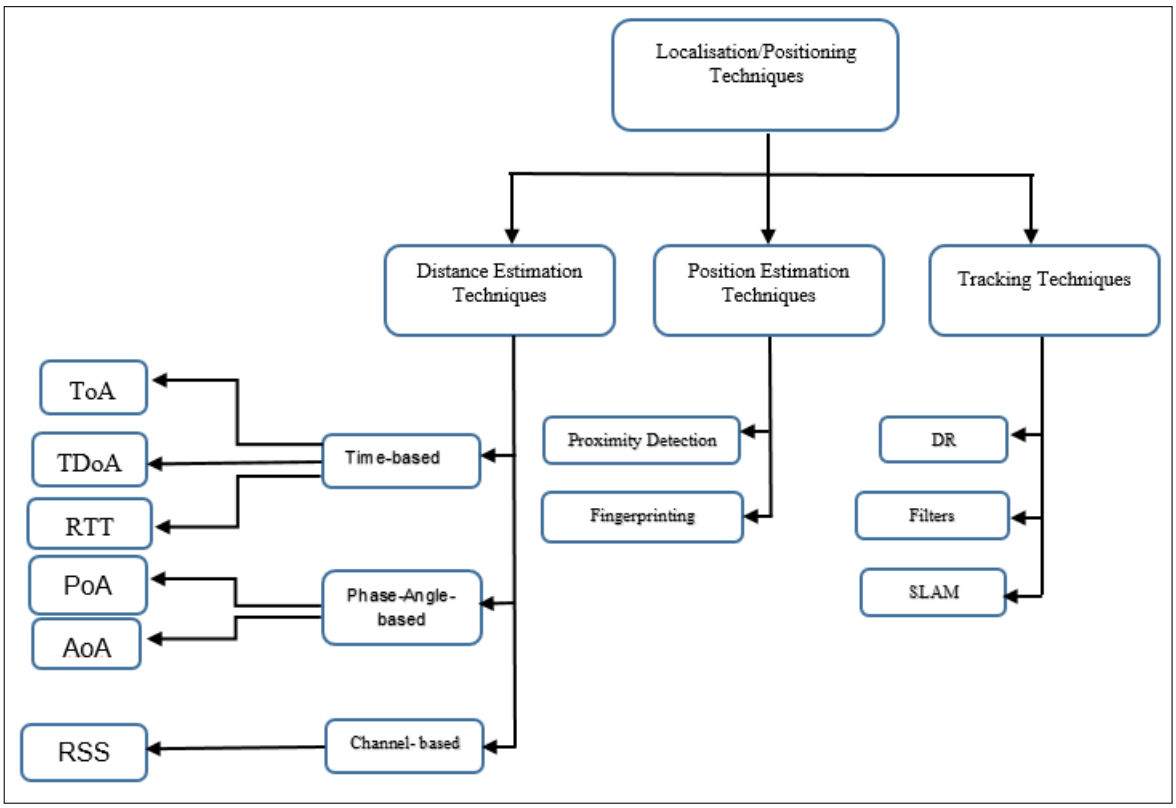


Figure 2.1: Classification of Localization/Positioning Techniques.

2.3.1 Time-Based Measurement Techniques

Time-based measurements are methods that estimate the time delay in signal propagation between transmitting and receiving nodes. These measurements, however, can be significantly affected by environmental factors. Key time-based measurements include ToA, TDoA, and RTT.

2.3.1.1 Time-of-arrival (TOA) Technique

ToA technique is a unidirectional method that measures the signal transmission duration [53] , which facilitates the estimation of the distance between the sending and receiving nodes, as depicted in Figure 2.2a. Accurate synchronization of the nodes' clocks and inclusion of timestamps in the exchanged packets within the network are prerequisites. The receiving node utilizes the timestamps of the received packets to estimate its distance d from the transmitting node, employing the following Eq (2.1) [54] :

$$d = (t_1 - t_2) * v \tag{2.1}$$

Where $t_1$and t_2 represent the transmitting and receiving times, respectively, and v is the signal velocity (e.g., 3×108 m/s for radio frequency (RF) signals or 350 m/s for ultrasound).

2.3.1.2 Time Difference of Arrival (TDoA) Technique

(TDoA) estimates distances by analyzing the travel time of signals between transmitters and receivers. Unlike ToA as depicte in Figure 2.2b, which requires knowledge of the exact time of transmission, TDoA simplifies the process by relying on the difference in travel times from multiple receivers [51]. This approach only requires synchronization between receivers, as the calculations depend on time or distance differences rather than absolute values. As a result, TDoA can achieve higher positioning accuracy than ToA when transmitting nodes are synchronized. However, its cost-effectiveness is limited to environments with dense node deployments, where such setups are feasible [55].The difference in propagation distances, denoted as $\triangle d_{i,j}$ at the receiving node can be calculated as Eq (2.2) :

$$\triangle d_{i,j} = d_i - d_j = v\,(t_i - t_0) - v\left(t_j - t_0\right) = v\left(t_i - t_j\right) = v\triangle t_{i,j} \tag{2.2}$$

Where i and j denote the distinct transmitting nodes, or disparate signals emitted from the same node, and v signifies the velocity of the signal.

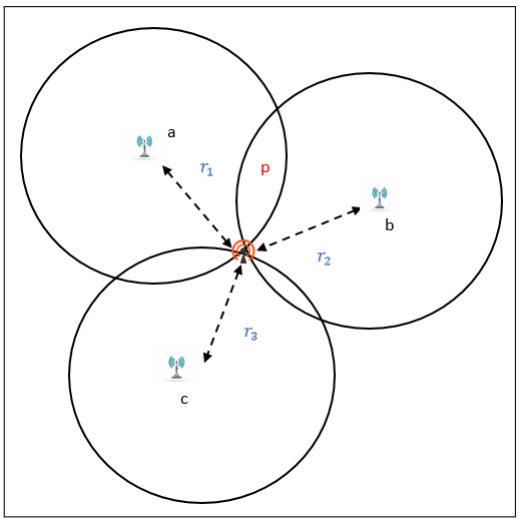
2.3.1.3 Round Trip Time (RTT) Technique

RTT technique is a time-based measurement method used to estimate the distance between two devices in a wireless network. This approach calculates the time taken for a signal to travel from the initiating device to the target device and back. By measuring the elapsed time and factoring in the signal propagation speed, the distance can be determined precisely, as illustrated in Figure 2.2c. RTT is particularly advantageous in environments where precise synchronization between devices is challenging, as it reduces the dependency on strict time synchronization. Widely used in modern positioning systems such as Wi-Fi and Ultra-Wideband (UWB) networks, RTT offers high reliability and accuracy in various indoor and outdoor settings [56].

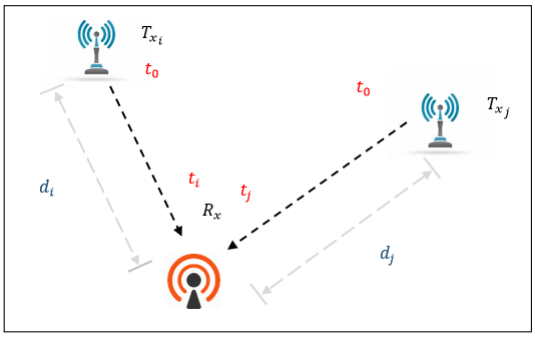
The distance between two nodes is then determined by Eq (2.3) :

$$d = \frac{(t_4 - t_1) - (t_3 - t_2)}{2} * v \tag{2.3}$$

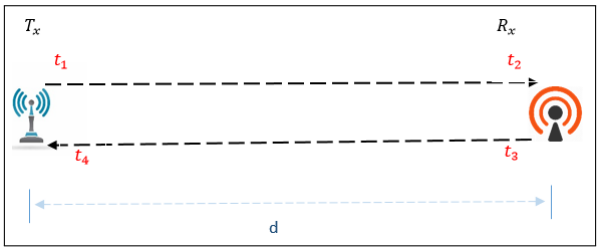
Where t_1 and t_4 represent the timestamps when the signal is transmitted and received at the transmitting node, while t_2 and t_3 correspond to the timestamps when the signal is received and retransmitted at the receiving node. The variable v denotes the speed at which the signal propagates.



(a)



(b)



(c)

Figure 2.2: Methods for Determining Location Using (a) ToA, (b) TDoA, and (c) RTT in Wireless Networks .

2.3.2 Angle-Based Measurement Techniques

Angle-based Approaches include phase comparisons, which compare the phase of the signal at the target node to the transmitted signal, and AoA (angle of arrival) measurements, which determine the angle between nodes by intersecting multiple signal directions.

2.3.2.1 Phase Difference of Arrival (PDoA) Technique

The PDoA technique utilizes the phase difference of the carrier signal to estimate the distance between the transmitting and receiving nodes. As illustrated in Figure 2.3a ,the incident signals reach the different antennas with a phase difference. Consequently, the phase difference of the signal received by multiple antennas at the receiver's end is utilized to estimate the distance between the transmitting and receiving nodes. However, the PDoA method is known to generally yield lower accuracy and is often combined with other measurement techniques, such as Time of Arrival, to improve the overall positioning precision [57].

2.3.2.2 Angle-of-arrival (AOA) Technique

AoA determines the incoming signal's direction relative to a reference device. As illustrated in Figure 2.3b, the reference device establishes a line oriented at the measured angle, indicating the assumed location of the target object. By combining multiple such lines from several reference devices, the target object's position can be determined at the intersection of these lines. This approach requires at least two reference points and two angle measurements (θ_1, θ_2). The advantage of AoA is that it does not necessitate time synchronization between the reference devices. However, the disadvantage is that it demands complex hardware to determine the angle of arrival [58].

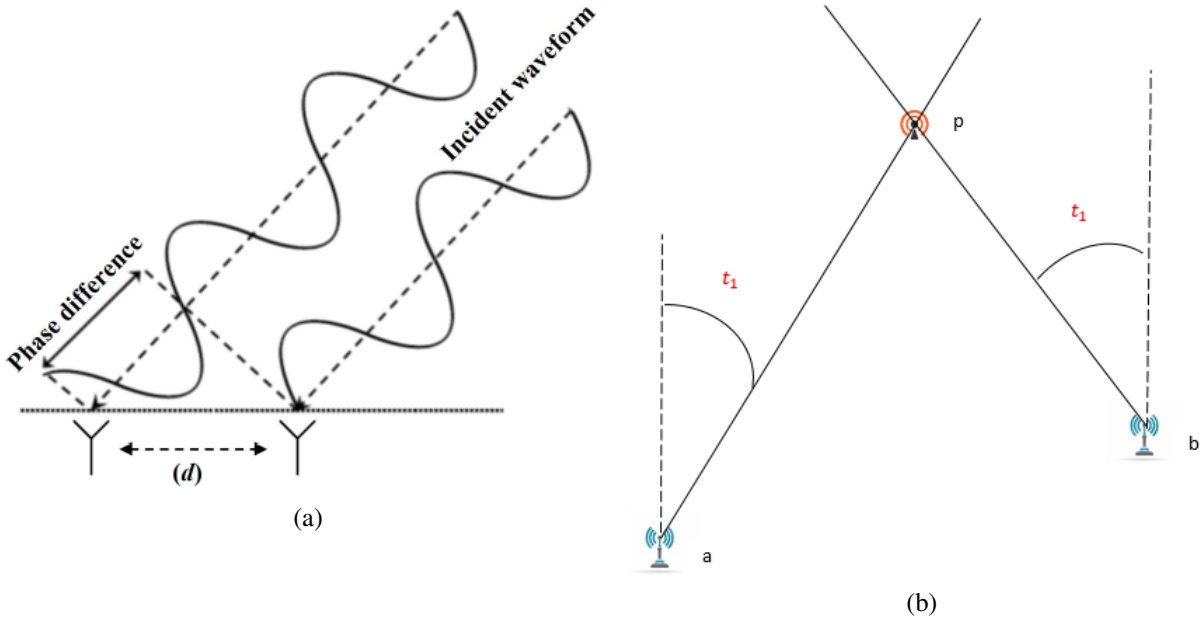


Figure 2.3: Angle-Based Localization Methods: (a) Phase of Arrival (PoA) and (b) Angle of Arrival (AoA) [34] .

2.3.3 Channel-Based Techniques

Channel-based measurements are fundamental to wireless communication systems, providing valuable insights into signal propagation and performance. These measurements include the LQI, RSS, and CSI. Among these metrics, we selected RSS as the primary focus due to its widespread use in the literature, particularly in smartphone-based localization systems. Its simplicity, broad accessibility on most devices, and effectiveness in distance estimation make it an ideal choice for developing reliable and practical localization solutions.

2.3.3.1 Received Signal Strength (RSS)

RSS refers to the field intensity of a signal at the receiving location. RSS is measured at the receiver, and the distance can then be estimated using a signal propagation model [59, 60] or other methods. The Friis propagation equation is commonly used [61], though more

complex models may also be applied in some cases. The RSS technique typically involves multilateration. The signal strength is inversely proportional to the distance d, and this relationship is expressed mathematically in Eq (2.4) :

$$P\,(d)\;[dBm] = P\,(d_0)\;[dBm] - 10n\log\left(\frac{d}{d_0}\right) \tag{2.4}$$

Where n is the path loss attenuation factor, $p\,(d_0)$ is the signal power at a reference distance d_0, measured in dBm, and d is the distance between the transmitting and receiving nodes. These parameters are typically determined through statistical evaluation methods, which involve collecting field measurements of RSS at predefined locations with known distances to the transmitting nodes.

2.3.4 Position Estimation Techniques

Position estimation techniques play a crucial role in determining the location of devices within wireless communication networks. These methods vary in complexity and accuracy, depending on the underlying approach, the density of nodes, and the environment. Two widely used techniques are Proximity Detection and Fingerprinting, which provide distinct methodologies for location estimation in both indoor and outdoor settings.

2.3.4.1 Proximity Detection

Proximity techniques are straightforward position estimation methods that provide relative location information based on the range of known transmitting nodes. The position of an unknown receiving node is estimated by detecting the strongest signal, and its relative location is derived by determining if it falls within the coverage area of a transmitting node's signal. The accuracy of proximity estimation depends on the density of the transmitting nodes, with each node's coverage forming a theoretical area, typically represented by a circle whose diameter corresponds to the signal strength as shown in Figure 2.4. Nodes within the signal range are classified accordingly, offering varying levels of precision, such as room-level accuracy indoors and cell-level accuracy outdoors [62]. These techniques are widely used in applications such as GSM-based localization, RFID-based anti-theft systems, and BLE beacons like iBeacon and Eddystone [63], which are found in environments like airports and hotels.

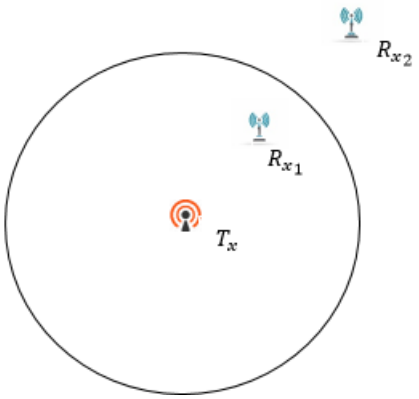


Figure 2.4: Proximity localization technique.

2.3.4.2 Fingerprinting

Fingerprinting is a technique used to determine the location of a device or person by comparing unique environmental signal "fingerprints" to a pre-recorded database [64].It is commonly applied in indoor localization and navigation systems, particularly in environments where GPS signals are unavailable or unreliable, as shown in Figure 2.5.

The fingerprinting process consists of two phases:

1. Offline Phase (Calibration): Signal data (e.g., Wi-Fi, Bluetooth, magnetic field, or sound) is collected at various known locations within the target environment. These readings, often referred to as "radio maps," are stored in a database along with their corresponding location coordinates.

2. Online Phase (Real-Time Localization):The system collects signal data at an unknown location and applies specialized algorithms, such as nearest-neighbor search or machine learning techniques [65,66], to match the new signal fingerprint with the stored database. The estimated location is determined based on the best match [53] .

Fingerprinting offers high localization accuracy, even in complex environments. However, it requires extensive calibration and is sensitive to environmental changes, which may affect its reliability over time.

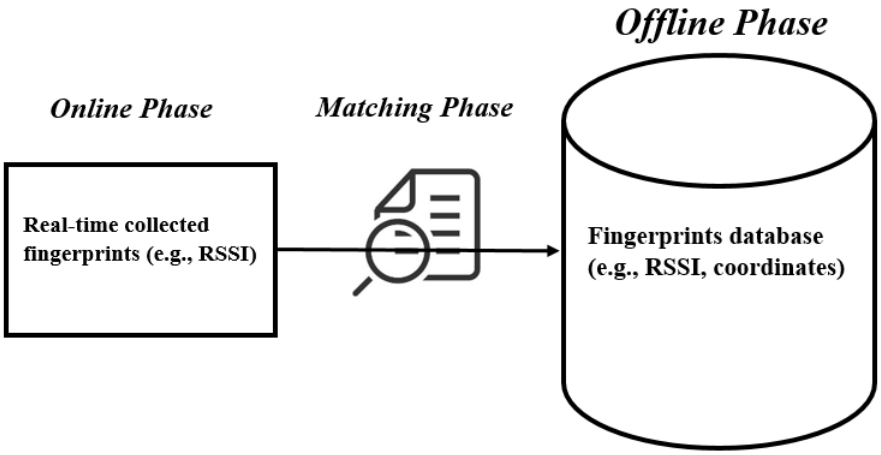


Figure 2.5: Fingerprinting localization technique [34].

2.3.5 Tracking Techniques

Tracking techniques are classified as continuous localization methods, designed to monitor an object's position over a defined period. These techniques typically rely on dedicated hardware that interacts with the surrounding environment, making the system's context crucial for achieving accurate position tracking. For outdoor applications, hardware such as satellites and cell towers is commonly employed, while indoor tracking predominantly utilizes sensors and cameras. Cameras, in particular, facilitate object tracking in three-dimensional space. This section examines three widely adopted tracking algorithms: Pedestrian dead reckoning, filtering methods, and SLAM.

2.3.5.1 Pedestrian Dead Reckoning

Dead Reckoning (DR) using smartphones estimates a pedestrian's relative position based on a known reference point, calculating changes from the last known location. Notably, PDR systems do not require any additional infrastructure within indoor environments, making them a highly suitable solution for indoor localization. Instead, PDR systems utilize inertial sensors such as accelerometers, magnetometers, and gyroscopes as inputs. Figure 2.6 illustrates the working architecture of a typical PDR-based indoor positioning system.

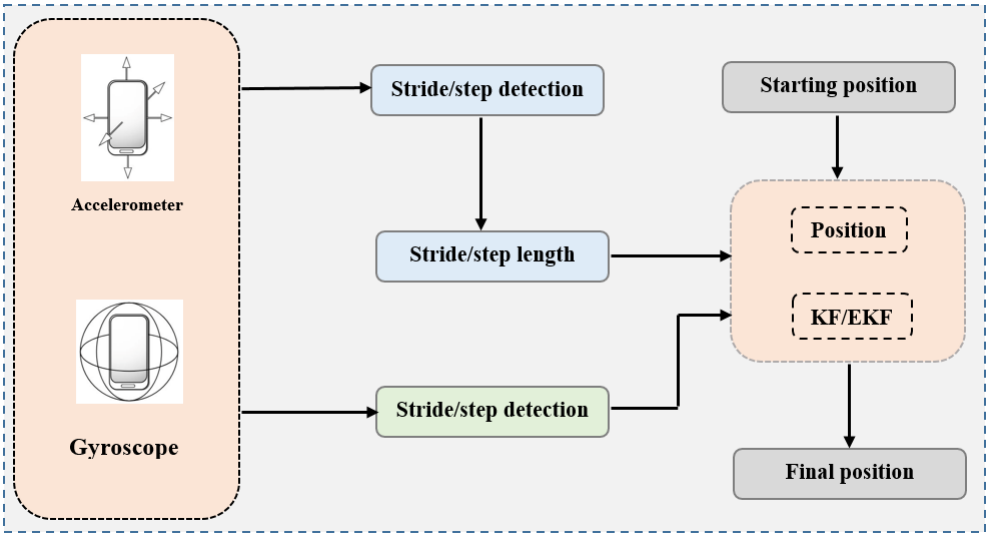


Figure 2.6: The working architecture of PDR [67].

(PDR) systems are classified into two main types: (INSs) and (SHS) [68].

(INSs) rely on data from the gyroscope and accelerometer to estimate position through a process called double integration. First, the accelerometer and gyroscope data are combined, and a rotational transformation is applied to convert measurements from the sensor's non-inertial reference frame (attached to the sensor) into the inertial reference frame. The resulting data is then integrated twice to estimate the position . INSs are used to track a variety of objects including Airplanes, missiles, space ships, vehicles Figure 2.7 illustrates the process flow of an INS.

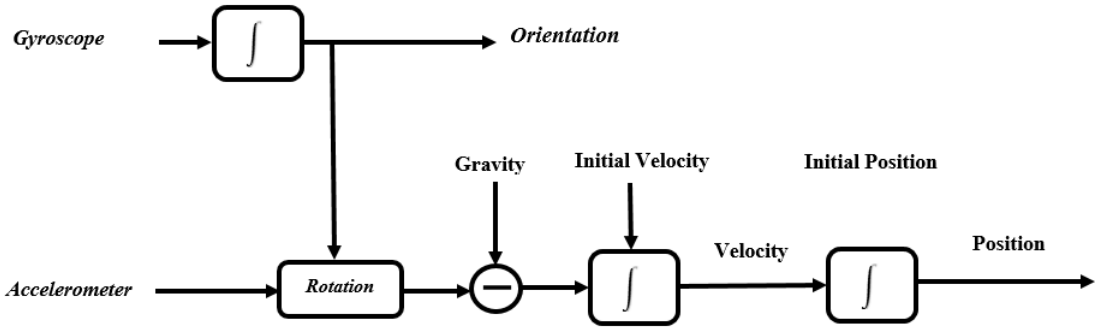


Figure 2.7: The process flow of INS [34].

In contrast, SHS detect a pedestrian's steps by analyzing acceleration data. Body movements create spikes in the acceleration signal, referred to as peaks, followed by a subsequent drop. To identify and count these peaks, various threshold-based methods can be utilized [69]. By integrating step counting with data from a compass or gyroscope, SHS calculates the pedestrian's heading and position. Figure 2.8 illustrates the process described.

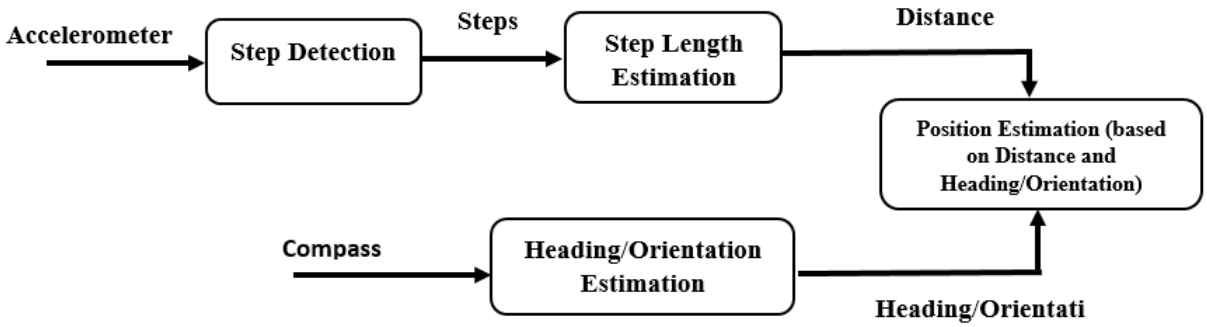


Figure 2.8: Step and Heading System (SHS) [34].

2.3.5.2 Filters

Filters, like the Particle Filter and Kalman Filter, provide a precise approach to tracking. These filters use a set of particles to represent the probability distribution of a stochastic or random process. Each particle corresponds to a hypothesis about the state variable, and the combined set of particles determines the final state estimate. The Bayesian state estimator, a notable example of Particle Filter usage, approximates the posterior distribution using discrete particles. Similarly, Monte Carlo methods, originally applied to robot localization, estimate a robot's position and orientation as it moves and senses its environment. In these methods, each particle represents the robot's possible state or position, starting with an unknown initial state represented by a uniform random distribution of particles across the space.

As the robot moves, the particles dynamically shift, enabling predictions of the new state and alignment with the actual state. This dynamic nature of the particles is a key aspect of the filtering process.

In contrast, the Kalman Filter (KF) plays a crucial role in estimating hidden variables based on uncertain or noisy measurements and predicting future system states using previous estimates. For example, hidden variables in a GPS receiver include its location and velocity, while measurements are derived from satellite signal timings. In some cases, such as in [70], KF is combined with fingerprinting to enhance (RSS) estimations. This approach shifts nearest-neighbor estimates closer to the actual path. KF is based on linear dynamical systems represented in the state-space format, assuming linear process and measurement models.

For non-linear systems, methods like the EKF and UKF are commonly utilized. In [71,72] discuss the successful implementation of the EKF for sensor fusion, demonstrating its effectiveness. Experimental results highlighted that the sensor fusion framework serves as a reliable localization approach for indoor environments. Additionally, a UKF-based algorithm was proposed in [73] for 3D indoor localization using smartphone sensor data.

2.3.5.3 Simultaneous Localization and Mapping (SLAM) Algorithm

The SLAM algorithm is a key technique that allows autonomous systems like robots or mobile nodes to map their surroundings while also determining their location within it. SLAM estimates the path of the platform and the positions of landmarks in real-time, without needing prior knowledge of the environment. The process involves mobile nodes

with changing states like position and orientation, and landmarks with fixed or slowly changing states. Probabilistic SLAM frameworks use observation and motion models to efficiently and consistently calculate prior and posterior distributions.

The observation model is represented as Eq (2.5) :

$$p\left(x_k, m \mid Z_{0:k}, U_{0:k}, x_0\right) \tag{2.5}$$

Where x_k denotes the state vector, m represents the landmark vector, $Z_{0:k}$ is the collection of all landmark observations, $U_{0:k}$ is the sequence of control inputs, and x_0 is the robot's initial state.

The motion model is expressed as Eq (2.6) :

$$p\left(z_k, m \mid x_k, m\right) \tag{2.6}$$

Where z_k is the observation of a landmark at time step k, and m corresponds to the landmark vector.

SLAM applications are diverse, from robot vacuum cleaners, which initially relied on random cleaning patterns, to advanced systems utilizing Vision SLAM (VSLAM) with infrared cameras for intelligent navigation and detailed environmental mapping [74]. While VSLAM improves operational efficiency, it is sensitive to lighting conditions [75]. Recent advancements integrate (IMUs) with SLAM, enhancing positional accuracy while increasing computational complexity. For example, IMU-SLAM has been applied effectively in pedestrian tracking for indoor navigation, particularly in emergency scenarios such as building evacuations or disaster response. The "FeetSLAM" algorithm [76], a collaborative SLAM technique, demonstrates how IMU-SLAM can enable precise localization in dynamic environments. These developments highlight SLAM's critical role in navigation, robotics, and real-time mapping, particularly in GPS-deprived indoor spaces.

2.4 Technologies for Indoor Localization

Indoor positioning technologies can be categorized based on the type of signal or methodology used. Below is a detailed classification of these technologies:

2.4.1 Radio Frequency-Based Technologies

RF-based technologies are widely used for indoor positioning due to their reliability, adaptability, and the prevalence of existing infrastructure. These technologies employ different frequencies and protocols for localization and can be tailored to specific use cases. Below is a summary of key RF-based technologies discussed in this section.

2.4.1.1 Wireless Fidelity (Wi-Fi) -Based Indoor Positioning

Wi-Fi-based localization systems have been widely studied for several decades. Starting with Microsoft Research's groundbreaking RADAR system, which utilized fingerprinting techniques, many similar systems have been developed to tackle the challenges of positioning and localization. Common techniques in Wi-Fi-based indoor localization include multilateration and fingerprinting, as well as methods like TOA), TDOA), and AOA see

section 2.3. However, these methods suffer from limitations such as low accuracy and high energy consumption. Fingerprinting techniques, on the other hand, are simple and easily adaptable for use with smartphones, providing an average accuracy of 2 to 3 meters without requiring costly hardware installation or configuration. Microsoft RADAR [77] was the pioneer in using fingerprinting with Wi-Fi infrastructure for localization, a concept that has since been explored, improved, and applied in numerous positioning systems [78, 79]. An example of the architecture of a Wi-Fi based indoor positioning system that is based on the fingerprinting approach shown in Figure 2.9 .

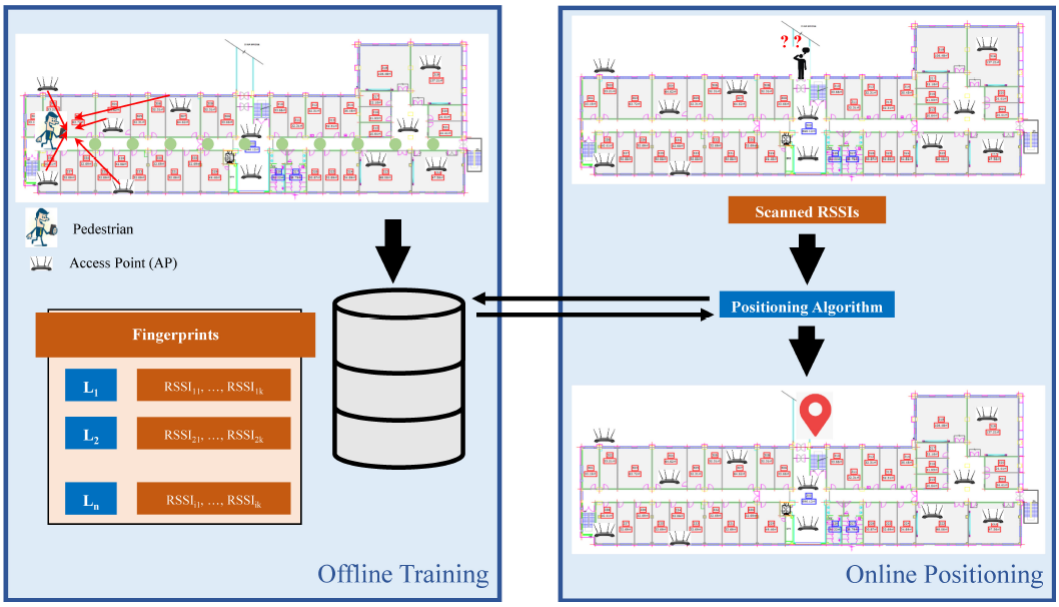


Figure 2.9: Structure of an Indoor Positioning System Using Wi-Fi and the Fingerprinting Method [67].

2.4.1.2 Indoor Localization Using Bluetooth

Bluetooth technology was initially designed to facilitate low-power wireless communication and operates within the Industrial, Scientific, and Medical (ISM) frequency band, specifically between 2.402 GHz and 2.480 GHz. It is classified into three categories based on its transmission range: Class 1, which supports communication up to 100 meters, Class 2, which operates within a 10-meter range, and Class 3, which is limited to 5 meters. Despite these classifications, the majority of Bluetooth-enabled devices function within an average range of 10–15 meters. Owing to its lightweight nature and extensive adoption, Bluetooth has been seamlessly integrated into mobile devices such as smartphones, making it a viable solution for indoor localization. Moreover, the affordability of Bluetooth-based localization systems is attributed to the use of low-cost transceiver microchips, thereby reducing overall development costs [80].

For localization purposes, Bluetooth technology primarily relies on two methodologies: triangulation and fingerprinting. These techniques utilize multiple signal parameters, including (LQ), (RSSI), (TPL), and Inquiry Result with RSSI, to enhance positioning accuracy [81]. Among these, fingerprinting is often preferred due to its higher reliability

compared to triangulation. This method employs a two-phase process, which aligns with similar approaches used in Wi-Fi-based localization systems.

In response to the growing demand for energy-efficient communication, Bluetooth technology has evolved into (BLE), which is specifically designed for short-range applications requiring minimal power consumption. Due to its simplicity, low power usage, and cost efficiency, BLE has been widely adopted across various domains. Notably, BLE-based localization systems have been successfully implemented in healthcare environments, where BLE beacons are used to monitor patient movements within hospitals [82].

Additionally, BLE technology has been explored for people detection [83], route guidance systems [84], and indoor navigation [85], demonstrating its versatility and effectiveness in real-world applications.

2.4.1.3 ZigBee

The ZigBee protocol, developed by the ZigBee Alliance, provides a cost-effective solution for low-data-rate wireless networks, characterized by exceptionally low power consumption. It is built upon the IEEE 802.15.4 standard, which defines both its physical layer and medium access control mechanisms [86]. Due to its energy efficiency and robust security features, ZigBee has been widely adopted in diverse applications, including home automation, urban traffic management, healthcare monitoring, and precision agriculture [87].

Beyond its broad applications, ZigBee has also demonstrated significant potential in indoor positioning systems. Its low cost, minimal power requirements, and the capability to extract RSSI values directly from transmitted packets eliminate the necessity for additional hardware, making it a practical solution for indoor localization. A typical ZigBee-based indoor positioning system consists of a network of sensors and utilizes wireless sensor network algorithms to estimate position. These positioning techniques primarily rely on RSSI values, employing methodologies similar to those used in Wi-Fi and Bluetooth-based localization, such as fingerprinting and propagation models.

For instance, Fang et al. [88] developed a system that integrates multiple ZigBee nodes and employs a hybrid localization approach combining propagation models and fingerprinting methods. Their study demonstrated that this integrated technique yields more accurate location predictions compared to standalone methods. However, while employing multiple localization algorithms enhances accuracy, it also introduces higher computational complexity and increased processing demands. Therefore, striking a balance between accuracy and computational efficiency remains a key challenge in ZigBee-based indoor positioning.

2.4.1.4 Radio Frequency Identification (RFID) Technology

RFID utilizes radio waves to allow specialized circuits to generate a response containing a unique identifier. Since these circuits can be affixed to individuals, animals, or objects, RFID serves as an effective identification method [89]. A typical RFID system consists of RFID readers and RFID tags, with the readers capturing data transmitted by the tags.

RFID tags, also known as "transponders", include a microchip and a printed circuit board functioning as an antenna [89]. These components enable the tag to emit radio signals, typically carrying unique identification information

Depending on their energy source, RFID tags can be categorized into three types [52]:

- Passive tags: Rely solely on the energy emitted by the RFID reader, captured via a small antenna, to transmit their response.
- Active tags: Contain their own power source and periodically transmit their ID signal.
- Semi-passive tags: Use a small battery but only transmit when activated by a reader signal.

RFID technology is widely applied across various domains, including personal or vehicle access control, retail security, equipment and baggage tracking, logistics, medical equipment management, and fast-food service automation [90]. For indoor positioning, RFID is particularly effective in scenarios where the user's location is only required at specific points, such as when passing through control zones like entry gates. In these cases, location is often represented in a logical form, such as "before the gate" or "inside the waiting room", rather than precise coordinates.

There are two primary configurations for RFID-based positioning systems:

1. Tag-based user tracking: The user carries an RFID tag, and stationary readers in the infrastructure detect its signal. This approach is more common due to the lightweight and low-cost nature of RFID tags, while readers are typically bulkier and more expensive.
2. Reader-based user tracking: The user carries a reader, and RFID tags are installed at specific locations within the environment. Although less frequently used, this setup has niche applications, such as indoor/outdoor navigation for visually impaired individuals.

A notable example of the first configuration is the LANDMARC system [91] . In LANDMARC, the tag is attached to the object or person being located. The system utilizes the signal intensity of RFID readers and calculates tag positions using the (k-NN) algorithm, achieving an accuracy of approximately 1 meter. However, limitations exist, as RFID readers do not directly measure signal strength; they only indicate whether a tag is "detectable" or "not detectable" . To overcome this, LANDMARC periodically scans power levels to estimate signal strengths, resulting in latency issues. Additionally, battery-powered tags may exhibit inconsistent behavior as battery levels deplete.

An example of the second configuration is the SeSaMoNet system implemented in Italy [92], designed for visually impaired users. In this system, the user carries an RFID reader at the tip of a cane, while passive RFID tags are embedded in sidewalks. Each tag is associated with a specific location and transmits its ID when detected by the cane. This ID is then linked to information about the location, which is relayed to the user audibly via a database. The system achieves optimal accuracy when the cane is positioned 20–25 cm from the tag.

2.4.1.5 Ultrawide Band (UWB) Technology

UWB is a wireless communication technology that transmits electromagnetic waveforms composed of very short pulses. It operates by sending pulses shorter than 1 nanosecond over a wide bandwidth, enabling high accuracy, typically within 20–30 cm [93]. While UWB signals can penetrate walls and effectively mitigate multipath issues, their accuracy tends to degrade significantly in indoor environments [94].

Additionally, UWB hardware is relatively expensive, making it a costly technology for large-scale applications [62]. In comparison to Wi-Fi, UWB's availability is limited to only a few smartphones [34]. UWB systems commonly utilize two methods to measure the distance between a target and a reference point: (ToA) and (TDoA). These measurement techniques are detailed in section 2.3 .

Bai and Lu [95] introduced an (IPS) based on UWB, comprising four fixed transmitters and several mobile users. The transmitters, synchronized through a time-division scheme, emit UWB signals to the mobile users. The location estimation is performed using a triangulation method that relies on measuring the TDoA between the transmitters and receivers. This system claims an accuracy of 1 meter when the UWB signal bandwidth is 528 MHz.

Furthermore, three commercial UWB-based localization systems using TDoA and AoA measurements, "Ubinense," "BeSpoon," and "DecaWave," were evaluated in a large industrial warehouse containing diverse obstacles that caused propagation loss and diffraction of the UWB radio signals [94]. Various methods and conditions, including LoS and NLoS, were tested. Overall, "DecaWave" demonstrated superior performance compared to both "BeSpoon" and "Ubinense."

2.4.2 Optical Technologies

Optical technologies utilize light for communication or sensing purposes, typically relying on electromagnetic waves in the visible, IR, or ultraviolet spectrum. These technologies are widely used for wireless communication, localization, and navigation .

2.4.2.1 Infrared Technology for Localization and Navigation

IR technology is widely utilized in (IPS) for localization and navigation [96, 97] . It operates using electromagnetic waves with wavelengths longer than visible light [98]. A basic IR system consists of a light-emitting diode (LED) that transmits infrared signals as bursts of non-visible light and a photodiode that captures and processes these signals to extract positional information [98]. These systems can function in either active or passive configurations, making them versatile for various navigation applications.

In the context of localization, IR systems rely on key properties of the emitted signals, such as directivity (the degree to which the signal is focused in a specific direction) and their interaction with obstacles, including reflection and scattering. While most IR systems require a direct (LOS) between the emitter and receiver for accurate operation, reflected signals may occasionally suffice to maintain functionality. However, the LOS dependency is a critical limitation, particularly in navigation, as obstructed paths can lead to undetected areas and reduced system reliability.

A significant application of IR technology in navigation was demonstrated by the Active Badge system, developed by Want et al. [96] , This system was designed to locate individuals within an office environment by equipping them with an IR badge that emitted a unique signal every 10 seconds. Sensors distributed throughout the space detected these signals and transmitted the data to a central computer, which processed and displayed the user's location. Although innovative, the system's LOS requirement and susceptibility to sunlight interference posed challenges for real-time navigation.

Further advancements in IR-based navigation systems were made by Gorostiza et al. [97], who proposed an active setup for determining the position of a mobile robot. This system measured distances using phase shifts relative to predefined reference points and applied a hyperbolic trilateration nonlinear equation system to compute the robot's location. This approach achieved remarkable precision, with an accuracy of less than 10 cm, making it a valuable tool for precise navigation in controlled environments.

2.4.2.2 Visible Light Communication for Localization and Navigation

VLC is an innovative technology that utilizes visible light to transmit data, making it a promising solution for localization and navigation. While any type of lamp can be used, LED lights are the most suitable due to their ability to switch on and off at high speeds, enabling data transmission through imperceptible flickering. Various modulation methods can be employed to encode the transmitted data. VLC has gained attention in (IPS) because it leverages existing artificial lighting infrastructure, offering a cost-effective implementation [99].

The core principle of VLC-based localization lies in encoding unique flicker patterns for each fixed lamp. A sensor, carried by the user, detects and decodes the light's modulation, identifying the dominant signal and associating the user's position with the corresponding lamp's vicinity (see Figure 2.10). This approach is particularly advantageous as it is non-intrusive, appearing as ordinary lighting fixtures mounted on ceilings.

The receiver in VLC systems can vary depending on the application. Common options include photodiodes, optoelectronic devices capable of measuring light intensity (e.g., photocells), or image sensors (e.g., cameras). Image sensors offer a significant advantage by simultaneously detecting signals from multiple lamps, enabling more precise localization.

Most VLC-based localization systems, such as those described in [100,101] and Zhang et al. [102], employ passive configurations, as the fixed lamps are stationary and connected to electrical networks. These systems have demonstrated impressive accuracy, with some achieving localization precision within 20 cm. Such capabilities make VLC a compelling technology for indoor navigation in environments that require high accuracy and minimal disruption.

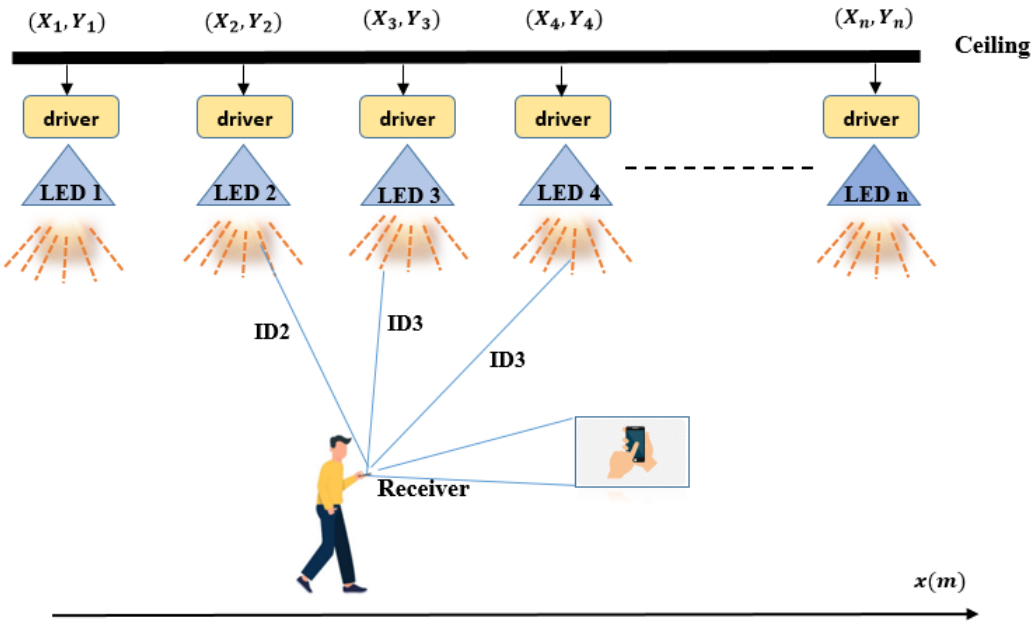


Figure 2.10: VLC approach [34].

2.4.3 Sound-Based Technologies for Localization and Navigation

Sound-based technologies have been widely explored for localization and navigation due to their ability to operate in various environments with minimal infrastructure requirements. These systems primarily rely on sound waves, which can be either ultrasonic (beyond the range of human hearing) or audible (perceivable by human ears). Both approaches have unique characteristics that make them suitable for specific applications in indoor and outdoor navigation.

2.4.3.1 Ultrasound Systems

Ultrasound systems utilize high-frequency sound waves, typically above 20 kHz, for localization. These waves are emitted by transmitters and detected by receivers, allowing for precise distance measurements based on the (ToF) principle. The ToF is calculated by measuring the time it takes for the sound wave to travel from the transmitter to the receiver. Using multiple ultrasonic sensors placed at known positions, systems can triangulate the user's location with high accuracy.

One advantage of ultrasound-based localization is its ability to provide precise distance measurements in small-scale environments. However, the performance of these systems can be affected by factors such as environmental noise, signal reflections, and obstacles, which may introduce errors or create blind spots. Despite these limitations, ultrasound technology has been effectively implemented in indoor navigation systems, a recent study proposed an innovative and cost-effective solution for the localization of mobile robots using ultrasound beacons, highlighting their capability for absolute positioning in constrained environments [103]. Another approach introduced the (SCAN) algorithm, which extends the coverage area of (ULPSs) and provides reliable navigation in extensive indoor spaces [104].

One notable advantage of ultrasound-based localization lies in its capacity to deliver highly accurate distance measurements, particularly in small-scale environments. However, the performance of such systems is often influenced by environmental factors, including noise interference, signal reflections, and physical obstacles, all of which can reduce the precision of the object's localization.

2.4.3.2 Audible Sound Technologies

Audible sound technologies leverage sound waves within the human hearing range (20 Hz to 20 kHz) for localization and navigation. These systems often use existing audio infrastructure, such as speakers or beacons, to emit signals that can be detected by microphones on mobile devices. Localization is achieved by analyzing the characteristics of the received audio signals, such as their intensity, phase, or frequency. Techniques like trilateration or fingerprinting are commonly used to determine the user's position [105].

A key advantage of audible sound-based systems is their compatibility with readily available hardware, reducing implementation costs. Additionally, these systems can provide dual functionality by combining localization with auditory feedback, making them particularly beneficial for assistive navigation. However, challenges such as interference from ambient noise and limited range need to be addressed to ensure robust performance. in the [106] demonstrated the application of sound-based localization using LSTM networks to assist visually impaired individuals, achieving practical results for navigation in real-world environments.

2.4.4 Inertial Sensors Technology

Inertial sensors are essential components in a wide range of navigation and localization systems, particularly for applications where external positioning signals like GPS are unavailable or unreliable [107]. These sensors measure the motion and orientation of a system, enabling the estimation of position and velocity over time. The primary inertial sensors used in navigation systems include accelerometers, gyroscopes, and, occasionally, magnetometers. Below is an overview of each type of sensor and its role in inertial navigation [108].

2.4.4.1 Accelerometers

Accelerometers measure the linear acceleration along specific axes. By detecting changes in velocity, they can estimate displacement and movement over time. When integrated, accelerometers provide valuable data for tracking the movement of an object in space.

2.4.4.2 Gyroscopes

Gyroscopes measure angular velocity, allowing them to estimate orientation and rotational movement. By tracking how much an object rotates over time, gyroscopes provide critical information about the orientation of a device, which is essential for accurate heading and orientation determination.

2.4.4.3 Magnetometers

Magnetometers measure the strength and direction of the Earth's magnetic field, providing a reference for heading or orientation. By comparing the magnetic field readings to a known map of the Earth's magnetic field, magnetometers can determine the direction of travel.

Recent advancements in inertial sensor technology have focused on enhancing sensor accuracy and mitigating drift through advanced calibration methods, improved sensor design, and the application of machine learning techniques. Emerging technologies, such as MEMS-based inertial sensors, are becoming increasingly compact and energy-efficient, making them suitable for portable and wearable devices [109].

2.4.5 Vision Positioning Systems (VPS)

Vision-based technology utilizes cameras or other scanning devices to detect distinct environmental features. VPS operate by comparing live image data with pre-stored frames or pre-constructed models, enabling the estimation of either relative or absolute positioning. This technology is widely accessible as it does not require additional infrastructure; however, it demands substantial storage capacity to house annotated image databases aligned with the environmental map [65]. Additionally, its effectiveness is limited by the need to run cameras at a low frame rate, making it more suitable for stationary or slow-moving targets [110]. For localization, VPS can achieve submeter accuracy, but its performance is sensitive to several factors. Small devices, for example, are prone to errors caused by pose and orientation changes. Moreover, the latency introduced by real-time communication between the server and smart devices, as well as slight shifts in the camera angle, can significantly alter the captured image, thereby impacting localization accuracy.

Recent advancements in VPS have focused on enhancing indoor navigation through vision-based methods. A notable study implemented an (IPS) leveraging computer vision techniques to improve the accuracy and reliability of indoor localization. This approach addresses some of the traditional challenges by utilizing advanced image processing and machine learning algorithms to better interpret environmental features, thereby enhancing positioning accuracy and reducing latency [111].

These developments indicate a promising direction for overcoming existing limitations in vision-based positioning systems, particularly in complex indoor environments.

2.4.6 Challenges and Limitations of Indoor Localization

Indoor localization technologies have emerged as critical tools for applications ranging from navigation in complex environments to asset tracking and smart building management. Despite their growing adoption and technological advancements, achieving precise and reliable indoor positioning remains challenging. Various factors, including environmental constraints, signal behavior, and system scalability, introduce limitations that impact the accuracy, efficiency, and usability of these systems. This subsection explores the primary challenges faced in indoor localization, including signal propagation issues, multipath interference, synchronization errors, and the inherent limitations of sensors such as inertial and camera sensors [31].

2.4.6.1 Signal Propagation and Attenuation

Indoor environments, such as office buildings, malls, and homes, contain walls, furniture, and other obstacles that can weaken or distort signals. Technologies like Wi-Fi, Bluetooth, or RF-based localization systems often experience attenuation due to these obstructions. For example, a Wi-Fi signal traveling through walls may lose strength, reducing the system's localization accuracy [112].

2.4.6.2 Multipath Interference and Line-of-Sight Requirements

Indoor localization systems are often affected by multipath interference, where signals reflect off surfaces such as walls, floors, or ceilings, creating multiple signal paths that lead to errors in estimating the position. Many systems also rely on (LOS) communication between transmitters and receivers, which may not always be feasible in cluttered environments [113].

2.4.6.3 Synchronization Issues

Systems relying on (ToF) or (TDoA) measurements require accurate synchronization between devices. Even minor timing discrepancies can cause significant errors in distance estimation, leading to inaccurate localization results [51].

2.4.6.4 Inherent Limitations of Sensors

The performance of indoor localization systems is heavily reliant on the accuracy and reliability of the sensors used. However, various types of sensors come with inherent limitations:

- Inertial Sensors: Inertial sensors, such as accelerometers and gyroscopes, are prone to accumulative errors or drift over time [114]. These sensors calculate position by integrating acceleration and angular velocity, but even small inaccuracies in measurements can compound, leading to significant errors in long-term localization without frequent recalibration or external corrections.
- Camera Sensors: Camera-based localization systems depend on image analysis to determine position. These systems are sensitive to lighting conditions [75], motion blur, and environmental changes, which can reduce their effectiveness. Additionally, camera sensors require significant processing power and storage for managing image databases or pre-constructed environmental models. Moreover, a slight change in camera angle or orientation can significantly alter the captured image, further impacting localization accuracy.

2.4.7 Trends and Emerging Technologies in Indoor Localization

Indoor localization technologies are continuously evolving, driven by improvements in wireless communication, sensor technology, and computational methods. One major trend is the increasing reliance on hybrid localization techniques [32], which integrate multiple

positioning methods, such as Wi-Fi, Bluetooth, magnetic field mapping, and inertial sensors, to enhance accuracy and overcome the limitations of individual approaches. (AI) and machine learning are playing a significant role in improving localization accuracy [31], particularly in fingerprinting-based methods, where deep learning algorithms can refine signal pattern recognition and adapt to environmental variations. (UWB) technology is gaining attention for its high-precision tracking capabilities, providing centimeter-level accuracy in indoor environments, which is particularly useful in industrial and healthcare applications [115]. (VLC) is also emerging as a promising alternative to traditional radio frequency-based approaches, leveraging LED lighting infrastructure for precise positioning while minimizing interference [116]. Additionally, (SLAM) is advancing, particularly in vision-based localization, allowing mobile devices to map environments dynamically while determining their position in real-time [117]. Furthermore, (BLE) beacons are being increasingly deployed for cost-effective and scalable indoor positioning in retail, smart buildings, and navigation for visually impaired individuals [118]. As these technologies continue to advance, future indoor localization systems will likely rely on a combination of these emerging methods to improve accuracy, efficiency, and adaptability across diverse environments.

2.5 Conclusion

Indoor localization has become an essential technology for applications where GPS is ineffective, including indoor navigation, asset tracking, emergency response, and smart environments. This chapter explored the state of the art in indoor positioning systems, providing a detailed classification of technologies and methodologies used for accurate localization. Various approaches, including radio frequency-based methods (Wi-Fi, Bluetooth, ZigBee, UWB, RFID), optical methods (IR, VLC), sound-based techniques (ultrasound, audible sound), vision-based localization, and inertial sensor-based systems, were analyzed.

Different localization methods such as time-based, angle-based, and channel-based techniques were examined, along with position estimation approaches like proximity detection and fingerprinting. Additionally, advanced tracking techniques such as (PDR), Kalman Filters, and (SLAM) were reviewed for their roles in improving accuracy and robustness.

Despite significant advancements, indoor localization systems still face several challenges, including signal attenuation, multipath interference, sensor drift, and infrastructure dependency. Hybrid localization techniques that integrate multiple approaches are increasingly being adopted to mitigate these limitations. Emerging trends such as (UWB) for high-precision tracking, machine learning-enhanced fingerprinting, and vision-based localization with AI-driven feature extraction show promise in overcoming existing challenges.

As research progresses, the future of indoor localization will likely involve artificial intelligence-powered solutions, energy-efficient (BLE) beacons, and increased reliance on (VLC) for precise positioning. The ultimate goal is to develop highly accurate, scalable, and cost-effective IPS solutions that operate seamlessly in complex and dynamic indoor environments, enhancing safety, accessibility, and efficiency across various applications.

Chapter 3

Design of a Step-Detection System for a Guide Dog Robot for the Visually Impaired

3.1 Introduction:

The rapid evolution of artificial intelligence, robotics, and sensor technologies has revolutionized assistive solutions for visually impaired individuals, enhancing their mobility and independence. Traditional aids such as white canes and guide dogs, while useful, have inherent limitations. Canes provide minimal environmental feedback, making navigation in unfamiliar settings challenging. On the other hand, guide dogs require extensive training, incur high costs, and have a limited working lifespan. Given that over 2.2 billion people worldwide suffer from vision impairments [119] , nearly half of which could have been prevented or treated, there is a pressing need for more adaptive, efficient, and cost-effective assistive technologies.

In light of these challenges, this chapter presents a step-detection-controlled robotic guide dog designed to facilitate navigation for visually impaired individuals. By leveraging a smartphone accelerometer, the system detects the user's walking pace and synchronizes the robot's movement accordingly. Integrated with Bluetooth communication and real-time obstacle detection, the system ensures seamless interaction between the user and the robotic guide. This chapter explores the technological landscape of assistive solutions, highlights recent advancements in robotics for visually impaired individuals, and details the development of the proposed robotic guide system, demonstrating its potential as a scalable and innovative alternative to traditional mobility aids.

3.2 Existing Technologies for Assisting Visually Impaired Individuals

Technological advancements have led to the development of various assistive tools aimed at improving the mobility and safety of visually impaired individuals. While traditional mobility aids such as white canes and guide dogs remain widely used, they have significant limitations, necessitating the introduction of more sophisticated solutions.

One of the most notable advancements is Electronic Travel Aids (ETAs) [120], which use ultrasonic, IR, or LiDAR sensors to detect obstacles beyond the reach of a white cane. These devices provide auditory, haptic, or vibrational feedback to guide users in real-time. Additionally, wearable assistive devices [121], such as smart glasses [122] and haptic belts, utilize computer vision and deep learning algorithms to recognize objects, detect hazards, and provide real-time audio cues.

Another growing area of research is smartphone-based navigation applications [7], which leverage GPS, inertial sensors, and computer vision to assist users with both indoor and outdoor navigation. These applications offer step-based navigation, real-time guidance, and voice-assisted feedback, making them an accessible and cost-effective alternative. Despite these advancements, challenges such as high costs, limited adaptability, and real-time environmental understanding persist, driving interest in robotic assistance.

3.3 Advancements in Robotics for Assisting the Visually Impaired

Robotics has emerged as a transformative technology in assisting individuals with visual impairments, offering innovative solutions to enhance mobility, independence, and quality of life. Recent advancements in (AI), computer vision, and sensor technology have enabled the development of robots and robotic devices that cater specifically to the needs of visually impaired individuals. These technologies are designed to navigate complex environments, provide real-time assistance, and facilitate daily tasks.

3.3.1 Navigation and Mobility Assistance

One of the most significant challenges for visually impaired individuals is navigating unfamiliar or dynamic environments. Robotic guide dogs and smart canes equipped with sensors and AI algorithms have been developed to address this issue. For example, the "GuideCane" is an early example of a robotic mobility aid that uses ultrasonic sensors to detect obstacles and guide users around them [123]. More recently, autonomous navigation systems like the "NavCog" app, developed by IBM Research, use smartphone sensors and AI to provide real-time auditory guidance for indoor navigation [124] .

3.3.2 Object Recognition and Retrieval

Robots designed for visually impaired individuals often incorporate object recognition and retrieval functionalities. For instance, the "EyeRing" is a wearable device that helps users identify objects by pointing at them and receiving auditory feedback [125] . Similarly, robotic systems like "RoboCart" assist users in grocery shopping by identifying products and guiding them through stores [126].

3.3.3 Social Interaction and Communication

Socially assistive robots (SARs) are being developed to provide companionship and facilitate communication for visually impaired individuals. Robots like Misty and its advanced version Temi are equipped with natural language processing (NLP) capabilities, enabling them to engage in conversations, read text aloud, and provide reminders for daily activities. For example, the Misty robot has been deployed in pilot programs to assist elderly individuals, including those with visual impairments, by reducing loneliness and offering health monitoring support [127] . In its extended form, the Temi robot enhances these functionalities with improved mobility, voice recognition, and interactive features, making it easier for users to control smart home devices and access information through voice commands. These robots are designed to seamlessly integrate into daily life, offering both emotional support and practical assistance to visually impaired individuals.

3.3.4 Wearable Robotics and Haptic Feedback

Wearable robotic devices, such NoorCam MyEye" use AI-powered cameras to recognize text, faces, and objects, relaying information to the user through audio feedback [128].

Additionally, haptic feedback systems, such as robotic gloves, provide tactile cues to help users interpret their surroundings and interact with objects more effectively [129].

3.4 Guide Mobile Robots as an Alternative to Guide Dogs

Guide dogs have long been a valuable aid for visually impaired individuals, enhancing their mobility and independence. However, training and maintaining these dogs require significant time, effort, and financial resources. Additionally, not all visually impaired individuals are willing or able to own a guide dog due to personal preferences, lifestyle constraints, or accessibility issues. As a result, researchers have explored robotic alternatives to provide similar assistance while overcoming these challenges.

3.4.1 Types of Guide Mobile Robots

Several types of robotic guide systems have been developed to meet the varying needs of visually impaired users. These systems generally fall into two main categories: wheeled robots and quadruped robots.

- **Wheeled Guide Robots**

Wheeled guide robots utilize motorized wheels to navigate environments efficiently [130, 131]. These robots are typically equipped with multiple sensors, including cameras, LiDAR, and ultrasonic sensors, to detect obstacles, identify paths, and recognize landmarks in real time [9]. In addition to their navigation capabilities, wheeled robots often feature audio-based interaction systems, such as speakers and microphones, allowing them to recognize user commands and provide verbal feedback.

Figure 3.1 demonstrates a wheeled guide robot that integrates a stereo camera, LiDAR, and motorized wheels, along with a tactile handle, enabling smooth navigation and effective guidance for visually impaired users.

- **Quadruped Guide Robots**

Quadruped robots are designed to mimic the movement and behavior of real guide dogs [132], offering a more intuitive and natural interaction for users. Like their wheeled counterparts, quadruped robots are equipped with an array of sensors that enable them to perceive and analyze their surroundings [133]. These robots rely on environmental mapping, path planning, and dynamic speed adjustments to guide users safely while avoiding obstacles. Their ability to replicate the gait of a biological guide dog makes them a more familiar and comfortable option for some visually impaired individuals [134–136]. Figure 3.2 presents a quadruped guide robot actively assisting a visually impaired person, demonstrating its ability to navigate hallways, detect obstacles, and provide real-time directional support.

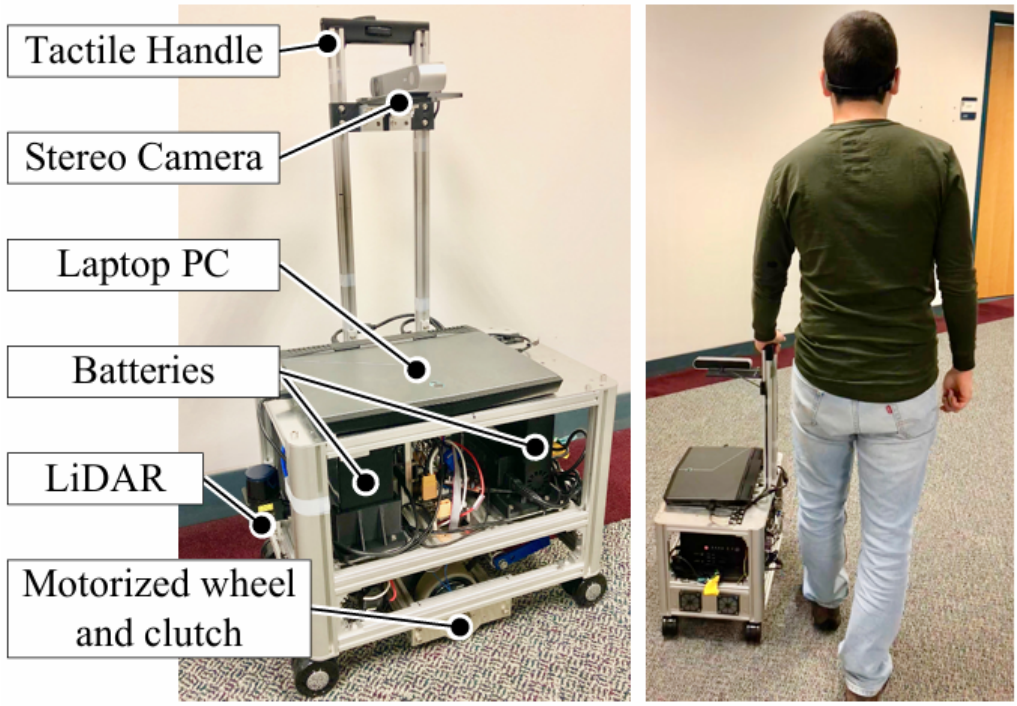


Figure 3.1: A wheeled guide robot featuring a stereo camera, LiDAR, motorized wheels, and a tactile handle for guiding visually impaired individuals [137].



Figure 3.2: A quadruped guide robot guiding a visually impaired individual by dynamically adjusting its movement based on environmental perception [138].

3.4.2 Challenges in Human-Robot Interaction

Despite their advancements, guide mobile robots still face significant challenges, particularly in socially acceptable navigation. One of the key issues is the concept of potentially

occupied spaces, which refers to areas that humans typically avoid entering, such as personal spaces, doorways [139], or areas where people are engaged in activities like watching television or conversing. A well-designed robotic guide must account for these social norms and adjust its navigation path accordingly to prevent discomfort or inconvenience for surrounding individuals [140].

Another challenge arises when robots attempt to navigate under obstacles such as desks or chairs. Although there may be enough physical space for the robot, it is often unnatural and impractical for users to follow such paths. Misinterpretation of navigable space can lead to collisions, making it crucial for robots to accurately assess and select appropriate paths that prioritize user safety and comfort [141].

3.4.3 Speed Control and User Adaptation

A major limitation of current guide mobile robots is their speed control mechanism. Many systems require users to either match the robot's speed or manually adjust the robot's pace [142]. However, visually impaired individuals often struggle with these adjustments due to their limited awareness of surrounding conditions. This lack of real-time situational awareness can lead to stress, especially if the robot moves into socially sensitive or uncomfortable spaces [143]. Future improvements in human-robot interaction and adaptive speed control are necessary to enhance the usability and acceptance of robotic guide systems.

3.5 Design and Development of the Robot Guide Dog

The development of an effective robotic guide dog requires a well-integrated combination of hardware and software components. The system must be designed to detect user movements, process environmental data, and navigate safely while ensuring real-time communication with the user. Achieving these objectives involves selecting appropriate sensors, actuators, and control mechanisms that enable seamless interaction and reliable operation.

This section details the core components of the robotic guide dog, beginning with the hardware architecture, including sensors, microcontrollers, and motion control systems. It then explores the software framework, focusing on step detection algorithms, navigation strategies, and user interaction methods.

3.5.1 Hardware Components and Sensors

The robot guide dog is designed as a mobile robotic system equipped with various sensors and hardware components to assist visually impaired individuals in indoor navigation. The system integrates real-time step detection, obstacle avoidance, and wireless communication to ensure seamless user interaction. Each component plays a crucial role in ensuring the robot's ability to navigate safely and synchronize its movement with the user's walking pattern. A schematic representation of these components can be seen in Figure 3.3.

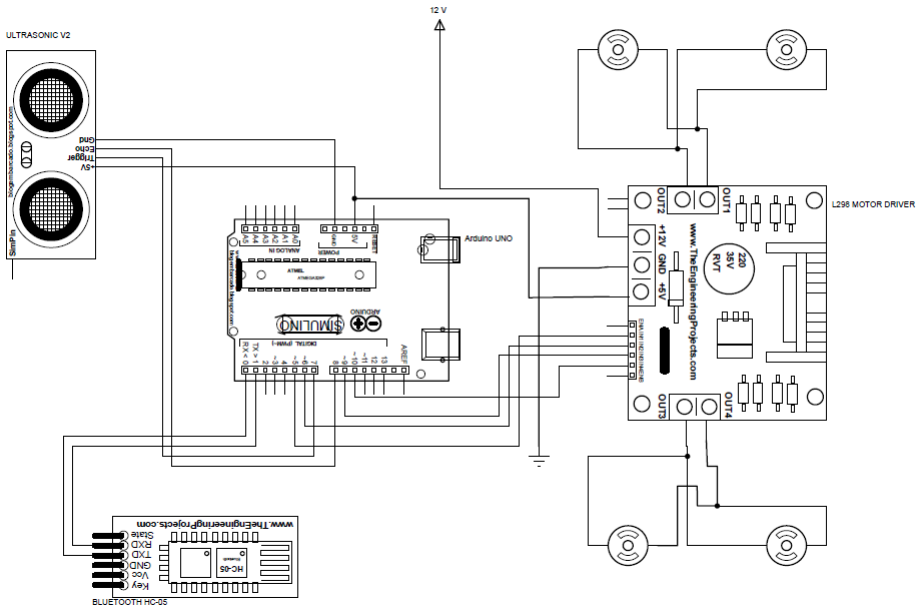


Figure 3.3: Configuration of the proposed Robot Dog Guide System.

3.5.1.1 Microcontroller and Processing Unit

To efficiently manage sensor inputs, motor control, and communication, the robot guide dog requires a central processing unit capable of handling multiple tasks simultaneously. The microcontroller serves as the brain of the system, ensuring that all components work together in real-time.

1. **Arduino Uno:** The Arduino Uno is the primary microcontroller used in this system. It is an open-source microcontroller board based on the ATmega328P chip, featuring 14 digital input/output pins, 6 analog inputs, and a 16 MHz quartz crystal. The Arduino Uno was chosen due to its ease of programming, extensive library support, and compatibility with various sensors and actuators. In this system, it processes sensor data, executes movement commands, and ensures real-time response to user input [144].

2. **Bluetooth Module (HC-05):**The HC-05 Bluetooth module enables wireless communication between the robot and the user's smartphone. It operates using a serial communication interface (UART), allowing seamless data exchange for real-time navigation control. When paired with the smartphone, the module transmits step detection signals and receives movement commands, ensuring the robot synchronizes with the user's walking pace [145].

3.5.1.2 Motion and Navigation System

For the robot guide dog to function effectively, it requires a reliable mobility and navigation system that ensures smooth movement and precise control. This subsystem consists of DC motors for locomotion and a power supply unit to sustain its operation.

1. **DC Motors:** The robot utilizes two high-torque DC motors, which are responsible for forward movement, turning, and speed adjustments. These motors are controlled by an L298N motor driver, which allows for bidirectional movement and speed regulation. The L298N driver efficiently manages motor power distribution, enabling smooth acceleration and deceleration based on the user's walking pace.

2. **Power Supply:**A stable power source is essential for uninterrupted operation. The system is powered by:

- 12V rechargeable battery that supplies energy to the DC motors, ensuring prolonged mobility.
- 9V battery dedicated to the Arduino Uno, preventing voltage fluctuations from affecting sensor readings and processing tasks.

3.5.1.3 Obstacle Detection and Avoidance

To ensure safe navigation, the robot is equipped with a multi-sensor obstacle detection system. This allows it to detect obstacles in real-time and avoid collisions while moving in dynamic environments.

Ultrasonic Sensors (HC-SR04): The HC-SR04 ultrasonic sensors detect obstacles at varying distances by emitting high-frequency sound waves and measuring the time taken for the echo to return. This allows the robot to:

- Identify objects within a 2cm to 400cm range with an accuracy of ±3mm [146].
- Adjust its path in real-time when an obstacle is detected.
- Stop movement immediately if an obstacle is too close, preventing accidental collisions.

3.5.1.4 Step Detection and User Synchronization

A critical feature of the robot guide dog is its ability to synchronize its movement with the user's walking pattern. This is achieved through step detection technology, allowing the robot to move at the same pace as the user.

1. **Smartphone Accelerometer:** The accelerometer embedded in the user's smartphone captures real-time motion data, detecting step frequency and walking speed. The data is then processed and transmitted via Bluetooth to the robot, ensuring that the robot's movement remains synchronized with the user.

2. **Step Detection:** Steps can be identified by the recurring pattern of vertical acceleration while walking. As mentioned in [147], several effective techniques, including peak detection, zero-crossing, autocorrelation, and stance phase detection, can be used to identify step occurrences. In [148], the authors empirically discovered that peaks in the variance of acceleration along the global Z-axis served as a reliable feature for detecting steps of a specific leg. A similar method was applied in this study. We utilize the acceleration measurements, which are projected into the vertical direction, to detect steps. The data are then processed using an Exponential Moving Average (EMA) [1] filter on the Android platform,The EMA filter is a recursive filtering technique that efficiently reduces noise in data. Its mathematical formulation is provided in Eq (3.1):

$$y(t) = \alpha x(t) + (1 - \alpha) y(t - 1) \tag{3.1}$$

In this equation, $y(t)$ signifies the output at time t, while $x(t)$ represents the input at the same time. The parameter α is a smoothing factor, constrained between 0 and 1, and $y(t - 1)$ corresponds to the output from the preceding time step.

The processed data is then used for step detection through peak detection [149] as shown in Figure 3.4. It is important to note that minor peaks in the acceleration signal result from residual sensor noise and the inherent complexities of human walking dynamics. To mitigate these effects in step counting, a relative threshold detection approach was implemented. Once a step is detected, a basic command directs the robot to move forward. However, if the robot's ultrasonic sensor detects an obstacle, it immediately halts and sends a notification to the smartphone app, alerting the user to the presence of the obstruction. subsection 3.5.2 will provide a detailed overview of the Android application developed to support this functionality.

3.5.2 Software Framework and Android Application

The Android application serves as the primary interface between the user and the robot guide dog, enabling seamless control, real-time feedback, and navigation assistance. This section delves into the design, functionality, and testing of the application, highlighting its key features and how it enhances the user experience for visually impaired individuals.

3.5.2.1 Android Application Design

- **User Interface (UI) Design:** The Android application was designed with a strong emphasis on accessibility, ensuring that visually impaired users can interact with it intuitively and efficiently. The UI incorporates several accessibility features, such as voice feedback, large buttons, and high-contrast color schemes, to accommodate users with varying degrees of visual impairment.

- **Voice Feedback:** The application provides real-time audio cues to guide users through its functionalities. For example, when the user opens the app, a voice prompt announces the available options, such as "Start Robot," "Stop Robot," or "Check Dis-

tance Traveled." This feature ensures that users can navigate the app without relying on visual cues.

- **Large Buttons and Simple Layout:** The interface is designed with large, tactile buttons that are easy to locate and press. The layout is kept simple to avoid overwhelming the user, with only essential functions displayed on the main screen. For instance, the main screen includes buttons for starting and stopping the robot, pairing the device via Bluetooth, and checking the distance traveled.
- **High-Contrast Color Scheme:** The application uses a high-contrast color scheme (e.g., black text on a white background or vice versa) to improve visibility for users with partial vision. This design choice ensures that the app is usable by a wider range of visually impaired individuals.

Figure 3.5 illustrates the main interface of the Android application, showcasing the large buttons for controlling the robot, the Bluetooth pairing status, and the distance traveled display.

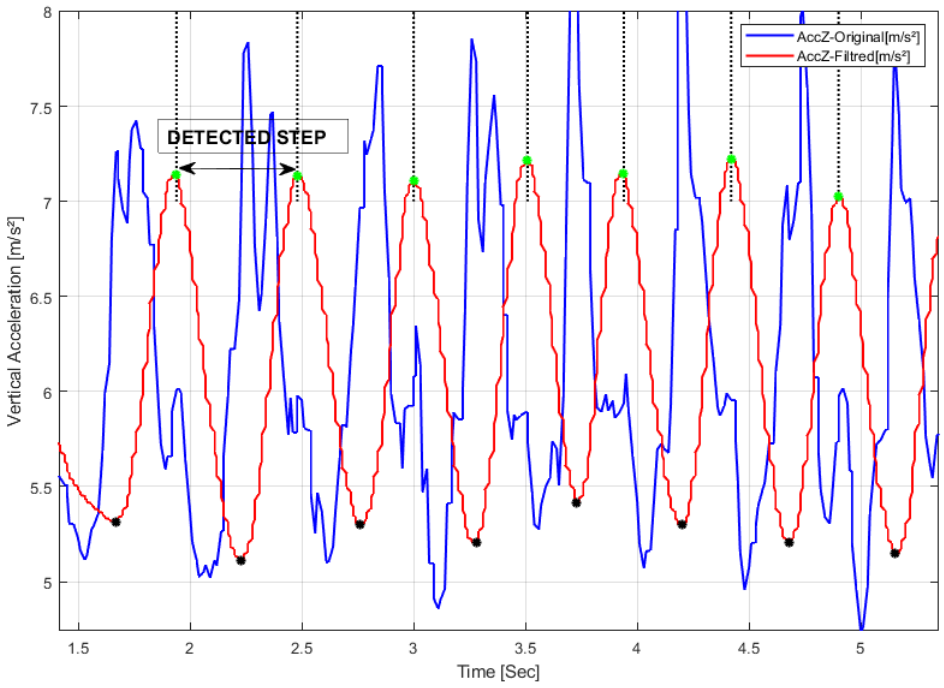


Figure 3.4: Step detection principle.

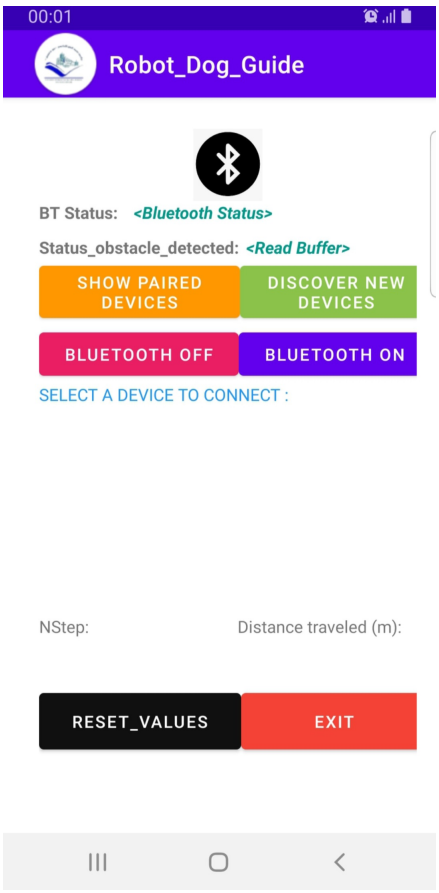


Figure 3.5: A screenshot of Step-Tracking Robot Guide Application.

3.5.2.2 Bluetooth Communication

The Android application communicates with the robot guide dog via Bluetooth, enabling real-time data exchange between the user's smartphone and the robot. The HC-05 Bluetooth module embedded in the robot facilitates this wireless communication, ensuring low-latency and reliable interaction.

- **Data Exchange Protocol:** The application uses a serial communication protocol to transmit data between the smartphone and the robot. Step detection data from the smartphone's accelerometer is sent to the robot, which then adjusts its movement accordingly. Similarly, obstacle detection signals from the robot's ultrasonic sensors are transmitted back to the smartphone, triggering alerts for the user. Figure 3.6 depicts the application's workflow, showcasing how it manages different functions to improve user interaction and overall experience.

- **Handling Connection Drops:** To ensure reliable communication, the application includes mechanisms to handle Bluetooth connection drops or interference. For example, if the connection is lost, the app automatically attempts to reconnect and notifies the user with a voice prompt such as, "Connection lost. Reconnecting now." Additionally, the app stores the last known data (e.g., step count, distance traveled) to prevent data loss during temporary disconnections.

- **Pairing Process:** The Bluetooth pairing process is simplified for ease of use. The app scans for nearby devices and automatically pairs with the robot guide dog when it is within range. Once paired, the app displays the connection status (e.g., "Connected" or "Disconnected") and provides voice confirmation to the user.

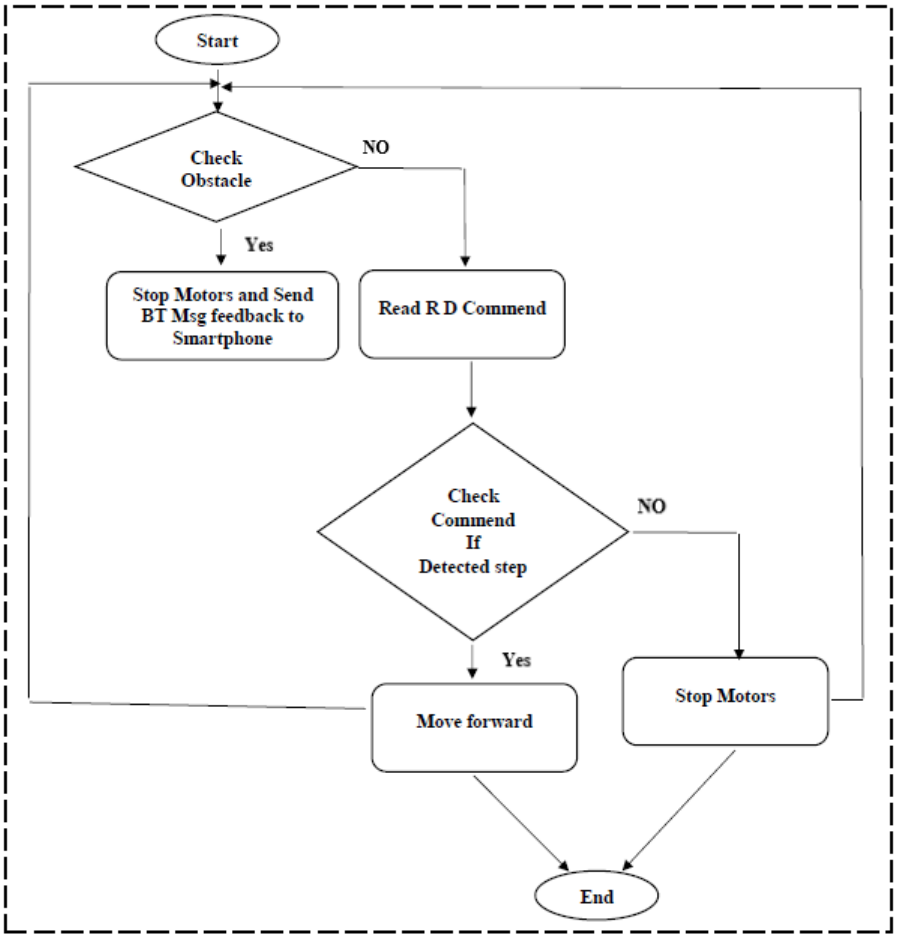


Figure 3.6: Flowchart Robot Dog Guide Functioning.

3.5.2.3 Real-Time Feedback and Alerts

- **Obstacle Alerts :** One of the key features of the Android application is its ability to provide real-time obstacle alerts to the user. When the robot's ultrasonic sensors detect an obstacle, the app immediately notifies the user through voice notifications and vibration feedback.

- **Voice Notifications:** The app uses pre-recorded voice messages to alert the user about obstacles. For example, if an obstacle is detected within 1 meter, the app might say, "Obstacle detected ahead. Please stop." The voice alerts are designed to be clear and concise, ensuring that the user can quickly understand and respond to the situation.

- **Vibration Feedback:** In addition to voice alerts, the app uses the smartphone's vibration motor to provide tactile feedback. For instance, a short vibration might indicate a minor obstacle, while a longer vibration could signal a more urgent situation, such as a collision risk.
- **Obstacle Prioritization:** The app prioritizes obstacles based on their proximity and potential danger. For example, stationary objects like walls or furniture are treated differently from moving obstacles like people or pets. The app uses different voice alerts and vibration patterns to distinguish between these types of obstacles, helping the user make informed decisions.

3.5.2.4 Step Tracking and Distance Calculation

The Android application tracks the user's steps and calculates the distance traveled, providing valuable feedback for navigation purposes. This feature is particularly useful for visually impaired users who need to monitor their progress during a journey.

- **Step Tracking:** The app uses the smartphone's accelerometer to detect steps, employing a peak detection algorithm to ensure accuracy. The algorithm filters out noise and false positives (e.g., from hand movements) by analyzing the vertical acceleration patterns associated with walking. Once a step is detected, the app updates the step count and displays it on the screen.
- **Distance Calculation:** The app calculates the distance traveled by multiplying the step count by the user's average step length. This value can be manually adjusted in the app's settings to accommodate individual variations in walking patterns. A constant step length provides a reasonable approximation of the average value [148] , This approach was chosen, and after conducting several tests, the step length was determined to be 65 cm. The calculated distance is displayed in real-time on the app's interface and can be announced via voice feedback upon request.
- **Navigation Assistance:** The step tracking and distance calculation features are integrated into the app's navigation system. For example, if the user needs to walk a specific distance (e.g., 50 meters), the app can provide voice updates at regular intervals (e.g., "You have walked 10 meters"). This functionality enhances the user's ability to navigate unfamiliar environments with confidence.

3.5.3 Application Testing and User Feedback

The Android application underwent extensive testing to ensure its usability and effectiveness for visually impaired users. The testing process included usability testing with visually impaired individuals, as well as technical testing to validate the app's performance under various conditions.

3.5.3.1 Usability Testing

The app was evaluated in a controlled indoor environment using a single subject imitating visual impairment. This single-subject scenario was selected for initial testing to assess the

method's feasibility and collect preliminary data. The participant was instructed to perform key tasks, including pairing the robot, starting and stopping the robot, and responding to obstacle alerts. Feedback was gathered through interviews and questionnaires, focusing on the app's ease of use, accessibility features, and overall effectiveness.

3.5.3.2 User Feedback

The single subject imitating visual impairment found the app's voice feedback and large buttons intuitive and easy to navigate. However, feedback indicated that the vibration feedback system could be improved by introducing more distinct patterns for different types of obstacles. Based on this input, the app was updated to incorporate a wider range of vibration patterns for enhanced user experience.

3.5.3.3 Technical Testing

The app's Bluetooth communication and step detection algorithms were tested under various conditions, including low signal strength and uneven walking surfaces. The results confirmed that the app maintained stable communication with the robot and accurately detected steps in most scenarios. However, occasional false positives were observed during rapid hand movements, leading to further refinements in the step detection algorithm to enhance reliability.

3.5.3.4 Improvements Based on Feedback

Based on user feedback, several improvements were made to the app, including:

- Enhanced vibration feedback with more distinct patterns for different obstacle types.
- Improved step detection accuracy by refining the peak detection algorithm.
- Added voice prompts for Bluetooth pairing and connection status.

3.6 Experimental Validation and Results

To evaluate the effectiveness of the robot guide dog system, a series of experiments were conducted in a controlled indoor environment. These tests focused on validating the system's step synchronization, obstacle detection, and overall performance in assisting visually impaired users. This section details the test environment, experimental procedures, results, and key findings.

3.6.1 Test Environment

The experiments were conducted in an indoor environment designed to simulate real-world scenarios faced by visually impaired individuals. The test area included various obstacles and challenges commonly encountered in urban and indoor settings, such as:

- **Furniture:** Tables, chairs, and desks were placed throughout the environment to simulate cluttered spaces.

- **Doorways:** Narrow doorways were included to test the robot's ability to navigate tight spaces.
- **Narrow Corridors:** The test area featured narrow corridors to evaluate the robot's maneuverability in confined spaces.
- **Dynamic Obstacles:** Moving objects, such as rolling carts and people walking, were introduced to test the robot's ability to handle dynamic environments.

The test environment was designed to replicate the challenges faced by visually impaired individuals in everyday life, ensuring that the robot guide dog could be evaluated under realistic conditions. Figure 3.7 showcases a practical demonstration of the developed robot guide dog system.

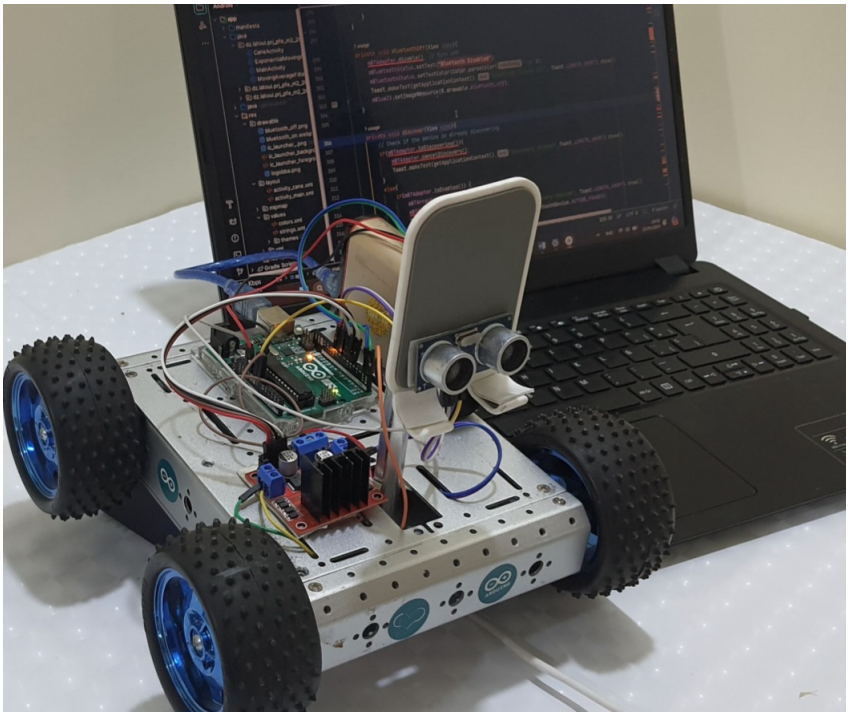


Figure 3.7: Prototype guide dog for the visually impaired.

3.6.2 Step Synchronization Tests

The step synchronization tests aimed to evaluate how well the robot matched the user's walking pace under different conditions. The tests were performed on flat surfaces Additionally, the tests were conducted with users walking at varying speeds, including slow walking, normal walking, and fast walking to assess the system's adaptability.

1. **Results:** The robot successfully synchronized its movement with the user's walking pace across all tested conditions. At a slow speed (around 0.5 m/s), it maintained a steady pace, ensuring user comfort. For a normal walking speed (approximately 1 m/s), the robot seamlessly adjusted its velocity, demonstrating adaptability to both normal and slow speeds. During speed walking (around 1.5 m/s), synchronization

was preserved, though slight delays were observed due to the additional processing needed to handle irregular step patterns.

2. **Challenges and Solutions:** One challenge encountered during testing was the occasional misalignment between the robot's movement and the user's steps, particularly during rapid changes in walking speed. To address this, the step detection algorithm was refined by incorporating a dynamic threshold adjustment mechanism. Specifically, the system adapts to the user's walking speed by adjusting the time interval between detected step peaks: for slower walking, the interval is significantly longer, while for speed walking, it becomes shorter. This enhancement improved the system's responsiveness to sudden changes in pace.

3.6.3 Obstacle Detection and Avoidance Tests

The obstacle detection and avoidance tests assessed the robot's ability to identify and navigate around obstacles in real-time. These tests involved both static obstacles (e.g., furniture, walls) and dynamic obstacles (e.g., moving people). In our system, an ultrasonic sensor is used for basic obstacle detection, enabling immediate hazard avoidance in controlled environments. We assume that the robot moves forward at a controlled pace, matching the user's stride along a straight path.

1. **Results:** The robot exhibited a high success rate in detecting and avoiding obstacles. For static obstacles, it accurately identified multiple objects and promptly halted movement to prevent collisions, achieving a 95% accuracy rate. In dynamic environments, the robot successfully detected moving obstacles and adjusted its movement accordingly, attaining an 85% success rate in collision avoidance. The ultrasonic sensors proved effective in detecting obstacles within a range of 2 cm to 400 cm, with an accuracy of ±3 mm.

2. **Handling Complex Environments:** in cluttered spaces, the robot efficiently navigated around multiple obstacles, demonstrating its ability to plan paths in real time. However, in highly dynamic environments with frequent moving obstacles, occasional manual intervention was required to prevent collisions. This underscores the need for further enhancements in the robot's dynamic obstacle avoidance capabilities.

3.6.4 Overall System Performance

The overall performance of the robot guide dog system was evaluated based on its ability to synchronize with the user's walking pace, detect and avoid obstacles, and provide real-time feedback. The system demonstrated several strengths, including:

- **Adaptive Navigation:** The robot's ability to synchronize with the user's walking pace and adjust its speed in real-time was a key strength, providing a seamless navigation experience.

- **Effective Obstacle Avoidance:** The robot's ultrasonic sensors and obstacle detection algorithms proved effective in both static and dynamic environments, ensuring safe navigation.
- **User-Friendly Interface:** The Android application provided intuitive control and real-time feedback, enhancing the user experience.

However, the system also had some limitations:

- **Dynamic Obstacle Handling:** While the robot performed well in static environments, its ability to handle highly dynamic obstacles (e.g., fast-moving people) was limited.
- **Battery Life:** The robot's battery life was sufficient for short-term use but may need improvement for extended navigation tasks.

Compared to traditional aids like canes and guide dogs, the robot guide dog system offers several advantages, including lower cost, ease of use, and adaptability to different environments. However, further improvements are needed to match the reliability and versatility of traditional guide dogs.

3.7 Discussion and Future Work

3.7.1 Key Findings

The research findings highlight the effectiveness of the step-detection-controlled robot guide dog in assisting visually impaired individuals. The system successfully synchronized with the user's walking pace, detected and avoided obstacles with high accuracy, and provided real-time feedback through the Android application. Figures 3.8 and 3.9 illustrate the robot's responses to step synchronization and obstacle navigation, further validating its capabilities. These results emphasize the potential of robotic assistive technologies to enhance mobility and independence for visually impaired individuals.

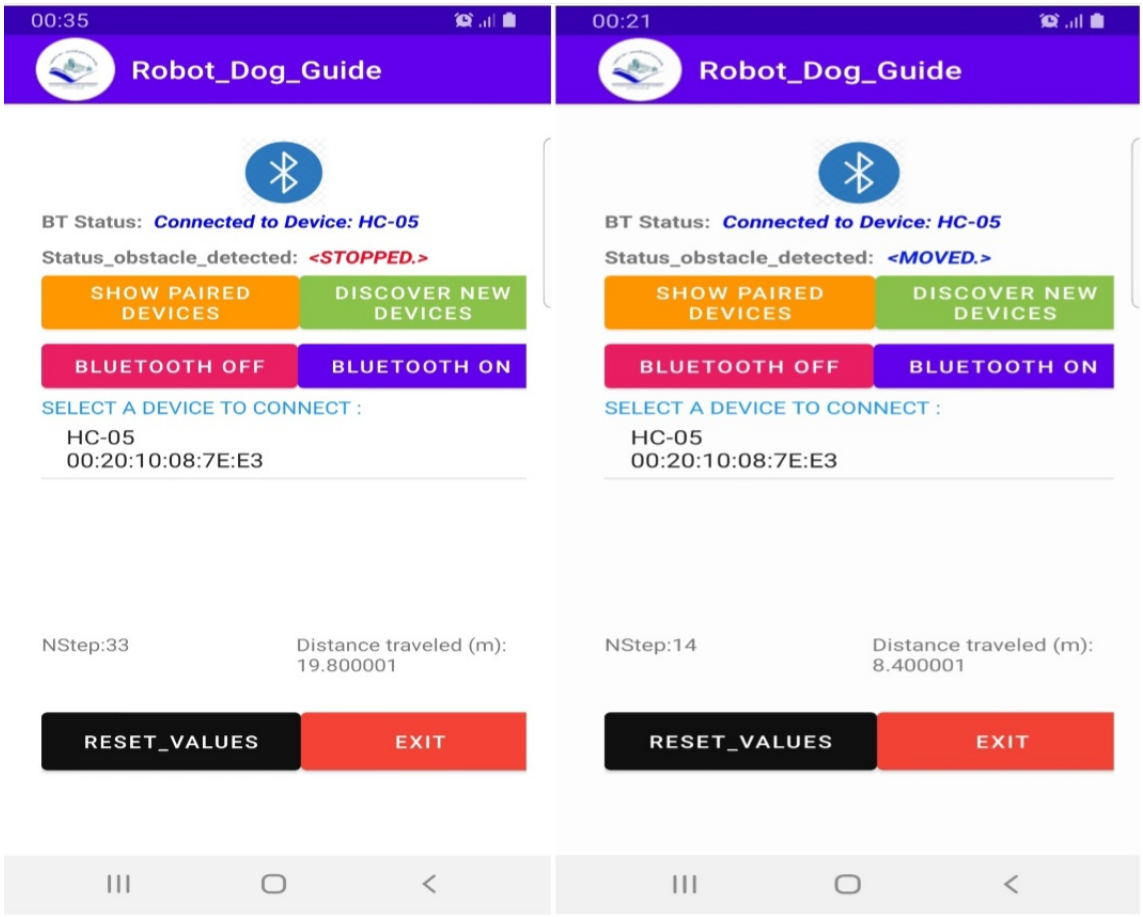


Figure 3.8: Robot Guide App Interface Obstacle Detection Test Scenarios.



Figure 3.9: Testing Step-Controlled Robot Guide for the Visually Impaired.

The implications of these findings are significant for the field of assistive robotics. The success of the robot guide dog system demonstrates the feasibility of integrating robotics, sensor technology, and mobile applications to develop innovative navigation solutions. This research paves the way for the development of more adaptive, reliable, and cost-effective assistive technologies tailored to the needs of visually impaired users.

3.7.2 Limitations

Despite its successes, the robot guide dog system has several limitations that need to be addressed:

- **Dynamic Obstacle Handling:** The system struggled to handle highly dynamic environments with frequent moving obstacles. This limitation could be addressed by integrating additional sensors, such as cameras or LiDAR, to improve environmental perception.
- **Battery Life:** The robot's battery life was sufficient for short-term use but may not be adequate for extended navigation tasks. Future iterations could explore more efficient power management systems or higher-capacity batteries.
- **User Adaptation:** Some users found it challenging to adapt to the robot's speed control mechanism, particularly during rapid changes in walking pace. Improving the system's adaptive speed control algorithms could enhance user comfort and usability.

3.7.2.1 Future Work

Future research directions for the robot guide dog system include:

- **Outdoor Navigation:** Expanding the system's capabilities to include outdoor navigation, integrating GPS and advanced mapping algorithms.
- **Enhanced Sensors:** Incorporating additional sensors, such as LiDAR and cameras, to improve obstacle detection and environmental perception.
- **AI and Machine Learning:** Integrating AI and machine learning algorithms to enhance the robot's navigation and obstacle avoidance capabilities, particularly in dynamic environments.
- **User-Centric Design:** Conducting further user testing to refine the system's design and improve its usability for visually impaired individuals.

These improvements could significantly enhance the system's performance and broaden its applications, making it a more viable alternative to traditional aids like canes and guide dogs.

3.8 Conclusion:

This chapter explored the evolution of assistive technologies for visually impaired individuals, emphasizing the limitations of traditional mobility aids and the potential of robotic solutions. Advances in electronic travel aids, wearable devices, and smartphone-based navigation applications have contributed to improving mobility, however, challenges such as cost, adaptability, and real-time environmental understanding persist. In response to these challenges, robotics has emerged as a promising alternative, offering solutions that

integrate AI, sensor technology, and computer vision to enhance navigation, object recognition, and social interaction.

The proposed step-detection-controlled robotic guide dog represents a novel approach to addressing these challenges. By synchronizing with the user's walking pace, integrating real-time obstacle detection, and utilizing Bluetooth communication for seamless interaction, the system enhances mobility and independence for visually impaired individuals. Our findings demonstrate the feasibility of robotics in assistive applications and open avenues for future improvements, such as refining AI-based navigation, expanding environmental adaptability, and incorporating multi-modal sensory feedback. As technology continues to advance, robotic guide systems have the potential to become widely accessible and transformative solutions for individuals with visual impairments.

Chapter 4

Development of an Accurate Smartphone-Based Approach for Indoor Pedestrian Localization Using ORB-SLAM and PDR Sensors

4.1 Introduction:

Accurately determining the position of pedestrians in indoor environments remains a significant challenge, particularly for visually impaired individuals who require precise navigation assistance. Unlike outdoor settings, where (GPS) technology provides reliable positioning, indoor environments suffer from signal attenuation, multipath effects, and occlusions, making GPS-based solutions inadequate for real-time indoor localization [150–152].

To address these challenges, researchers have explored various alternative positioning methods, including wireless technologies such as Bluetooth beacons [2, 153, 154] , Wi-Fi routers, and (UWB) transmitters [68, 155], While these methods offer notable benefits, they often require additional infrastructure, leading to substantial installation and maintenance costs. Other approaches, such as (PDR) and (SLAM), have also been investigated. PDR, which relies on smartphone sensors like accelerometers and gyroscopes to estimate user movement, is prone to cumulative drift over time. On the other hand, SLAM-based methods, such as ORB-SLAM, use camera input to map environments and track user movements but struggle in low-texture areas or under varying lighting conditions. These limitations highlight the need for a more robust and integrated solution.

This chapter presents a smartphone-based indoor pedestrian localization system that integrates ORB-SLAM with PDR sensor data to mitigate the limitations of standalone approaches. By employing a Kalman filter for back-end sensor fusion, the system enhances localization accuracy and robustness in dynamic indoor environments. The proposed approach is specifically designed to assist visually impaired individuals by providing a cost-effective, real-time localization solution using only a smartphone. Additionally, the system has potential applications in various domains, such as healthcare, retail, and industrial settings, where accurate indoor positioning is critical.

The rest of the chapter is structured as follows: Section 4.2 Reviews related works in the field of indoor localization relevant to our contribution. Section 4.3 details the proposed ORB-SLAM and PDR fusion approach. Section 4.4 describes the experimental setup and methodology used for evaluating the system. Section 4.5 presents and discusses the results obtained from various test scenarios. Finally, Section 4.6 concludes the chapter and suggests future improvements to the proposed system.

4.2 Background and Literature Review

The widespread adoption of smartphones has led to a growing interest in mobile-based positioning and navigation technologies. This demand is driven by the portability and multi-sensor capabilities of modern smartphones, which enable a range of location-based services. In this section, previous research on smartphone-based indoor pedestrian localization systems, including (PDR) and (SLAM), is reviewed.

4.2.1 Pedestrian Dead Reckoning (PDR) Approaches

PDR is a technique for indoor and outdoor localization that has gained significant popularity. It relies on sensors commonly found in smartphones, such as gyroscopes, magnetometers, and accelerometers [156, 157]. PDR utilizes these sensors to track the user's move-

ments and estimate their position, particularly in scenarios where the phone is attached to the user and hinders natural movement while walking. Addressing the limitations of conventional PDR, Pan et al. [158]proposed a two-phase algorithm that utilizes accelerometer data to detect step patterns and estimate step counts. Concurrently, the SmartPDR system [159] divides heading direction estimation into four cases to detect turning points, thereby mitigating drift errors caused by sensor inaccuracies over time. However, it should be noted that this enhancement is only effective in experimental setups with closed loops. Poulose et al. [109] introduced a position-estimation algorithm that combines accelerometer, magnetometer, and gyroscope data to estimate pitch, roll, step length, and heading direction using a Kalman filter framework. Despite these advancements, achieving accurate and efficient indoor localization with smartphone-based PDR approaches remains challenging, particularly for applications targeting visually impaired individuals, as localization errors often exceed one meter, compromising safety.

4.2.2 Visual SLAM for Indoor Localization

SLAM-based approaches rely on visual data to construct a map of the environment while simultaneously tracking the user's position. ORB-SLAM, a widely used feature-based method, has proven effective for real-time applications due to its computational efficiency [15]. However, these systems often face challenges such as cumulative global drift and tracking failures in low-texture areas or under varying lighting conditions. Researchers have attempted to enhance SLAM robustness through various techniques. For instance, Zhong et al. [11] introduced a modified version of the Real-Time Edge-Based SLAM (RESLAM) framework, integrating inertial sensor data to enhance positioning accuracy in challenging indoor environments. Similarly, Dong et al. [12] enriched the sliding window optimization technique by incorporating step velocity and step length factors, significantly improving localization performance. Earlier, Klein et al. [160] Proposed Parallel Tracking and Mapping (PTAM), a pioneering SLAM method that separates tracking and mapping processes and employs keyframe selection to reduce computational complexity. These innovations have laid the groundwork for subsequent developments in SLAM technology.

4.2.3 Sensor Fusion for Enhanced Localization

Sensor fusion techniques have been widely explored to enhance the accuracy and robustness of indoor localization systems. For instance, the extension of ORB-SLAM to visual-inertial SLAM (ORB-SLAM 3) [161] integrates IMU data with visual information using a sophisticated non-linear optimization approach, improving performance in dynamic environments or areas with sparse visual features. The Multi-State Constraint Kalman Filter (MSCKF) method [162] fuses IMU and vision data using the Extended Kalman Filter (EKF), leveraging camera pose measurements at different time instances to reduce computational complexity. Additionally, the PS-VINS system [10] integrates IMU measurements, smartphone imagery, and GNSS data to provide comprehensive solutions for both indoor and outdoor localization. Despite these advancements, many of these solutions have yet to be validated with low-cost sensors, such as those found in smartphones, and challenges such as computational complexity and sensitivity to environmental conditions remain.

4.2.4 Contributions of This Work

In response to the limitations of existing smartphone-based localization systems, we propose a framework that integrates ORB-SLAM and PDR-inertial techniques, leveraging a smartphone's camera and IMU sensors. By combining the strengths of both methods, our framework aims to achieve robust and accurate indoor position estimation, offering a practical solution for visually impaired individuals who rely solely on their smartphones for navigation [16]. This approach represents a significant step forward in addressing the challenges of cumulative drift, low-texture environments, and sensor inaccuracies, ultimately enhancing the safety and reliability of indoor localization systems for vulnerable user groups.

4.3 A smartphone-based ORB-SLAM-Inertial fusion approach

The indoor navigation system proposed in this study is specifically designed to support visually impaired individuals by providing an efficient and reliable positioning solution through their smartphones. The primary objective is to enhance their mobility and independence in indoor environments. This section elaborates on the details of the proposed localization framework.

As shown in Figure 4.1, the system combines visual and inertial sensing techniques to achieve accurate position estimation. The initial position of the user is derived from the smartphone's onboard inertial sensors, particularly the (IMU), which consists of an accelerometer, gyroscope, and magnetometer. The data collected from these sensors help estimate the user's heading direction and step length. To improve the reliability of the position estimation, an (EKF) is utilized to integrate the sensor data effectively.

In addition to inertial sensing, the smartphone's camera plays a crucial role in localization. The ORB-SLAM algorithm is applied to process visual data, allowing the system to detect and track key feature points in the environment. These tracked features are used to generate a map of the surroundings, which further enhances the accuracy of position estimation.

To ensure a more precise and robust localization outcome, a Kalman filter is implemented to merge the outputs from both the inertial sensors and the camera. This fusion approach leverages the strengths of both modalities—compensating for individual limitations—to refine position estimates dynamically. The integration of both sensing methods results in a more stable and accurate positioning system, particularly suited for real-time indoor navigation.

The following subsections provide a comprehensive breakdown of each component of the proposed approach, as depicted in Figure 4.1.

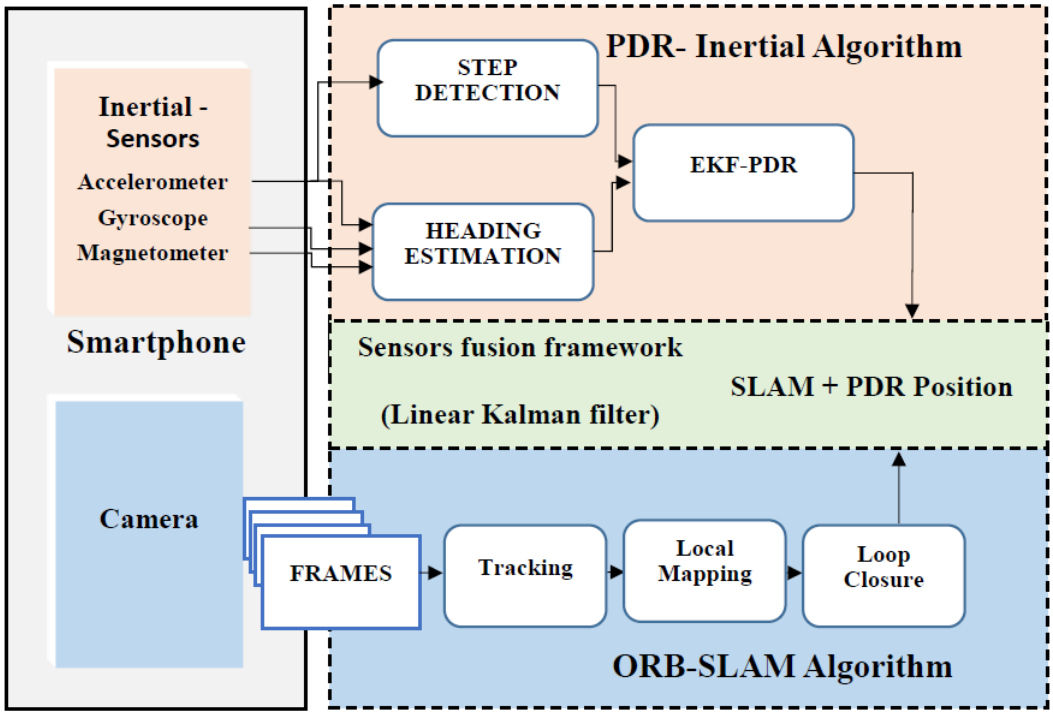


Figure 4.1: Architecture of the proposed navigation system.

4.3.1 ORB-SLAM Smartphone Camera Integration

This section describes the integration of the ORB-SLAM algorithm, as illustrated in Figure 4.2 , which is widely used for (SLAM) in monocular camera systems. ORB-SLAM is preferred due to its efficiency in real-time applications and its robustness against variations in lighting and viewpoint. Unlike traditional methods that rely on SIFT or SURF [163] , ORB features are computationally lightweight, making them well-suited for smartphone-based applications [164]. The ORB-SLAM system is composed of three main components: tracking, local mapping, and loop closure. A concise overview of each module is provided below.

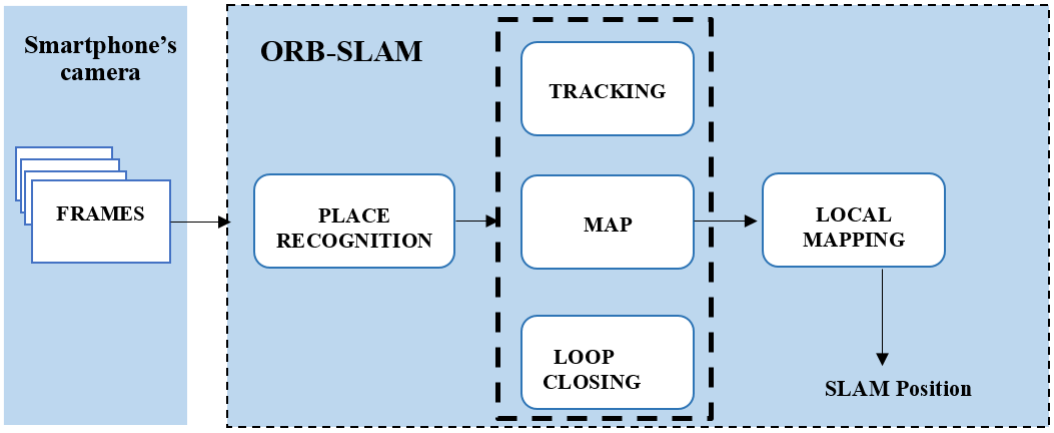


Figure 4.2: Flowchart of the ORB-SLAM-based positioning algorithm utilizing a smartphone camera.

4.3.1.1 Tracking Module

The tracking module plays a critical role in estimating the camera's position for each frame and determining when to insert new keyframes. To refine the camera's pose, a motion-only bundle adjustment (BA) technique is employed. This technique involves the optimization of 3D coordinate points and camera parameters to minimize re-projection error, which denotes the discrepancy between observed and predicted points across multiple frames. In the ORB-SLAM system, the motion-only BA specifically optimizes the camera's movement without modifying the map structure, thereby enhancing the accuracy of camera pose estimation during tracking.

Initially, the camera's motion is estimated by matching features between the current frame and the previous one. In the case of tracking failure, a pose detection mechanism is triggered. This mechanism involves a comparison of the current frame with a database of previously stored keyframes, facilitating global relocalization by identifying familiar locations and re-establishing the camera's position within the map.The following Figure 4.3 provides a visual illustration of feature matching between two consecutive frames. In the figure, red circles represent keypoints detected in the first frame, while green crosses indicate keypoints in the second frame. The yellow lines connecting these keypoints serve to illustrate the feature matching process. This process is critical for accurately estimating camera motion and maintaining reliable tracking within the SLAM system.

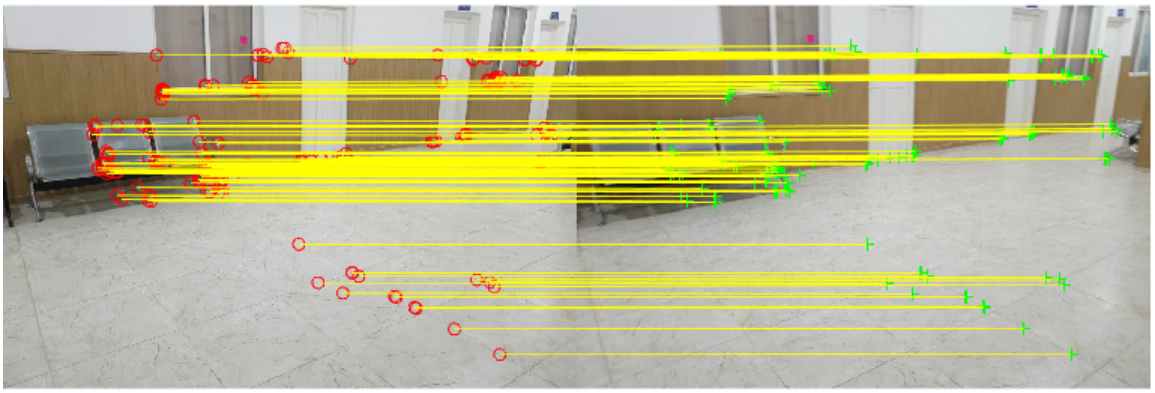


Figure 4.3: An example of feature matching from Path 1, as detailed in the experimental section, is presented.

4.3.1.2 Local mapping module

The local mapping module is responsible for constructing a local map once the camera poses and feature maps are initialized. This process utilizes a covisibility graph, which consists of keyframes linked by shared map points. In this graph, nodes represent keyframes, while edges indicate common points between them. The alignment of local map points is achieved through a process known as reprojection, which involves the projection of 3D points back onto the 2D image plane of the keyframes. Subsequently, the camera pose is optimized based on these matches, ensuring the estimated poses accurately align with the observed features.

The system autonomously determines when to add new keyframes to the local mapping process. This determination is influenced by factors such as the camera's distance tra-

versed, its angular velocity, and the number of pixels tracked. By evaluating these criteria carefully, the system strategically adds keyframes to maintain both accuracy and efficiency in the mapping process.

4.3.1.3 Loop Closing Module

The loop closing process is responsible for detecting previously visited locations as new keyframes are added. This step is essential for maintaining long-term localization accuracy, as it enables the system to recognize when the camera revisits known areas, thereby correcting cumulative drift. When a loop is detected, the system performs a similarity transformation to evaluate the positional drift that has accumulated within the loop, as an illustration of our loop closing process, Figure 4.4 presents a detected loop, highlighting the inliers that contribute to the similarity transformation. This transformation aligns the current pose with an earlier recorded pose, highlighting any discrepancies that have emerged over time.

To further reduce drift, the system merges duplicated feature points by integrating corresponding points from overlapping regions. This process refines the map structure, making it more accurate and consistent. Additionally, a pose graph optimization technique is applied to ensure global consistency. This optimization method adjusts the positions of all keyframes across the map, minimizing overall errors and distributing corrections evenly. As a result, the reconstructed environment remains coherent and precise. Further details on ORB-SLAM can be found in [15].

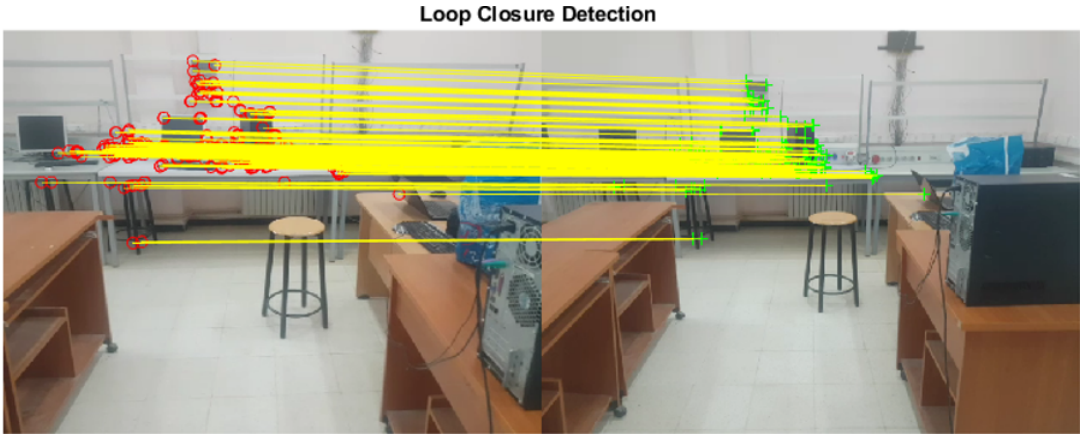


Figure 4.4: An example of a detected loop in the laboratory is shown, where the inlier correspondences supporting the identified similarity transformation are highlighted.

4.3.2 PDR Inertial Sensors Integration

The proposed indoor localization system adopts the PDR approach, as shown in Figure 4.5 . This method utilizes data from the smartphone's magnetometer, accelerometer, and gyroscope to track user movement. The core functionalities of this process include step detection and heading estimation, which are outlined below.

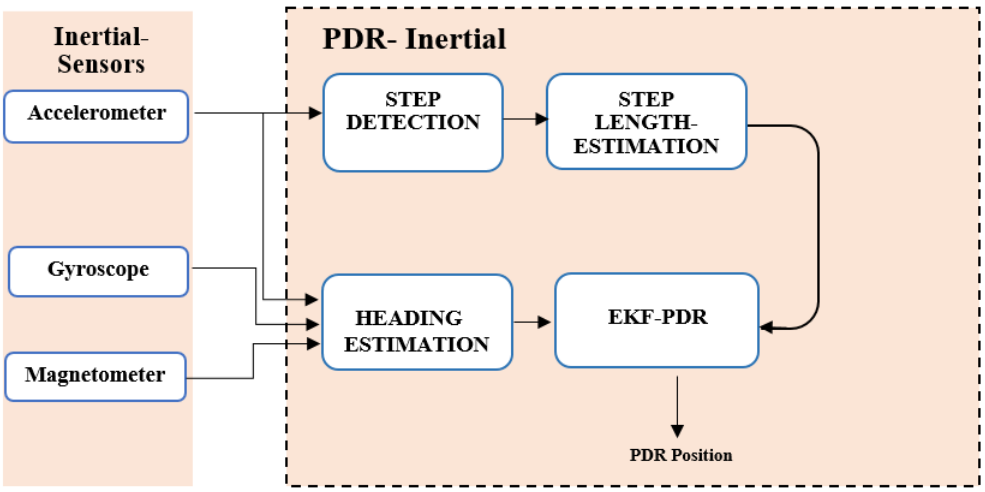


Figure 4.5: Diagram of the PDR-Inertial positioning algorithm that leverages a smartphone's IMU.

4.3.2.1 Step Detection

Step detection is performed using a peak detection algorithm applied to acceleration data, specifically analyzing vertical acceleration measurements to recognize individual steps. Initially, the data is processed through a sliding window filter (size = 5) to smooth out fluctuations. After filtering, a peak detection method is applied to identify steps accurately.

To compensate for sensor noise and the irregularities in human walking patterns, a dynamic thresholding technique is used. This method continuously adjusts the step detection threshold based on the baseline acceleration values and their variations, ensuring reliable step counting. By distinguishing true steps from noise, the system effectively adapts to different walking styles.

An illustration of this process, demonstrating the results for Path 1, is provided in Figure 4.6 , as detailed in the experimental section.

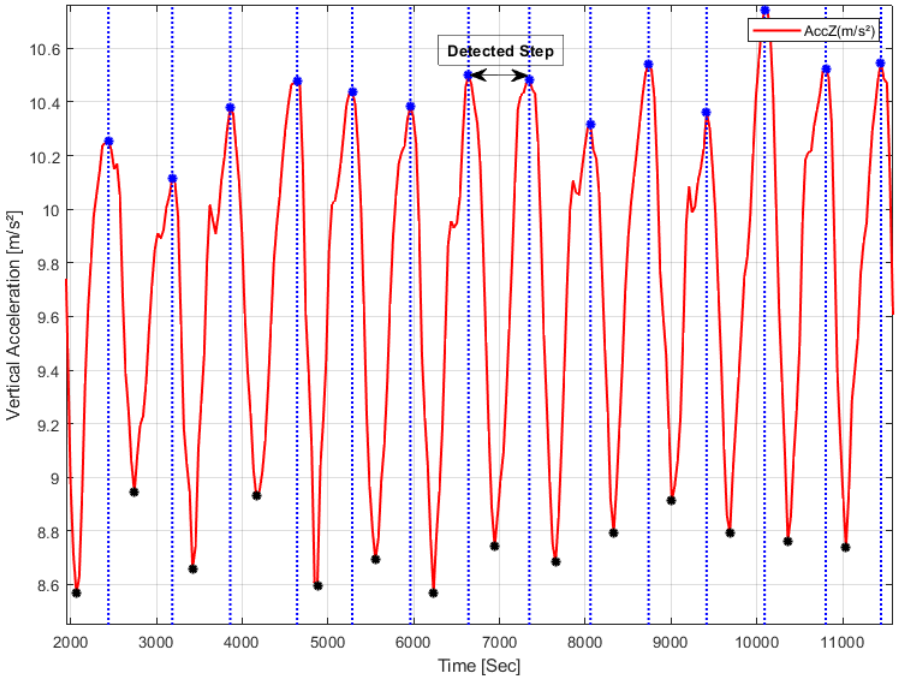


Figure 4.6: Step identification through the analysis of vertical acceleration variations along the (Z-axis).

4.3.2.2 Step Length Estimation

Several approaches are available for step length estimation, including linear, nonlinear, and constant models. In this study, the Weinberg model [165] is adopted, utilizing the following step length estimation Eq (4.1):

$$S_k = K \times \sqrt[4]{Accz_{Max} - Accz_{Min}} \tag{4.1}$$

Where K is a constant, $Accz_{Max}$ and $Accz_{Min}$ represent the minimum and maximum acceleration values recorded along the Z-axis during step k. It is important to highlight that the value of K was determined empirically, and our analysis indicated that setting K=0.5 produced optimal results.

4.3.2.3 Heading Determination

Since heading estimation plays a more critical role over step length estimation [149], we employ a sensor fusion approach that integrates data from both the gyroscope and magnetometer to achieve accurate heading estimation. This method effectively compensates for the individual weaknesses of each sensor: the gyroscope can capture rapid orientation changes but suffers from drift over time, while the magnetometer provides a stable

long-term orientation reference relative to Earth's magnetic field, though it is susceptible to local magnetic distortions.

Before utilizing both the gyroscope and magnetometer, we first combine data from the accelerometer and gyroscope. The accelerometer is used to correct the tilt angles (pitch and roll), ensuring that the orientation quaternion remains accurate and drift-free. This initial fusion process provides a stable short-term orientation estimate, which is then further refined by integrating magnetometer data.

To achieve precise heading estimation, a Kalman filter is applied, as described in [109]. This filter effectively merges the high-frequency data from the gyroscope with the absolute orientation information from the magnetometer, producing a more reliable and accurate pedestrian heading estimation. The results of this sensor fusion approach, particularly the Azimuth estimation for Path 1, are illustrated in Figure 4.7 in the experimental section.

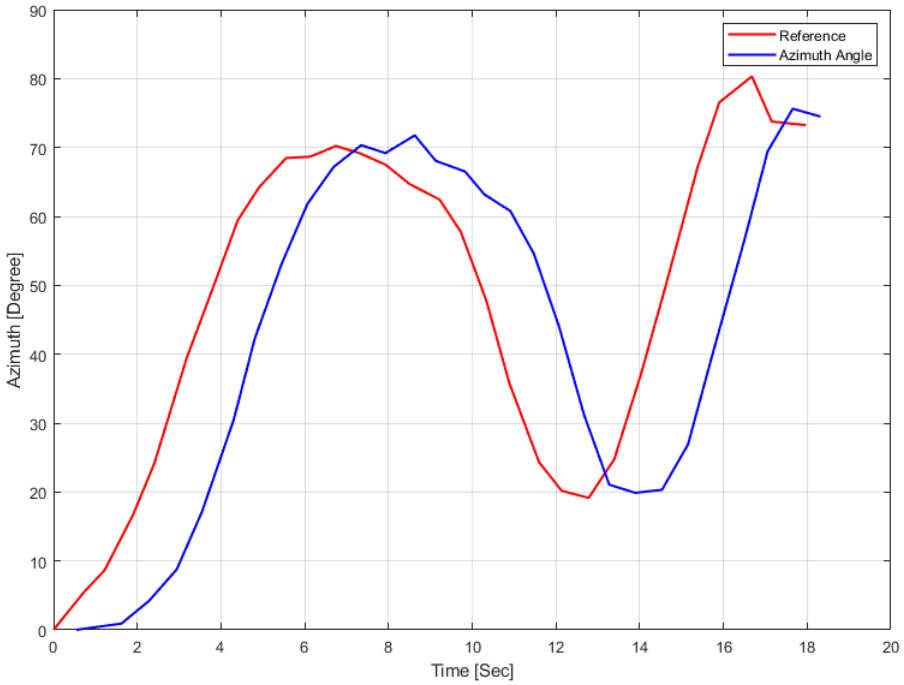


Figure 4.7: Estimation of the azimuth angle.

Once the step length and heading estimates are obtained from the PDR inertial system, they are further refined using the (EKF) framework. This integration enhances the overall accuracy and robustness of the localization system. The proposed approach, outlined in this chapter , is inspired by the methodology presented in [149] .

4.3.2.4 Pedestrian Position Estimation

The state vector X_k in Eq (4.2) represents the pedestrian's position and heading at a given time step k. In this context , x_k and $y_k$correspond to the coordinates along the east and north directions, respectively, within the local East-North-Up (ENU) reference frame, while α_k denotes the heading angle.

$$X_k = \begin{pmatrix} x_k \\ y_k \\ \alpha_k \end{pmatrix} \tag{4.2}$$

When a step is detected at time k, the estimated heading direction is fed into the filter, leading to an update of the a priori state estimate $\hat{X}_k$ based on Eq (4.3):

$$\hat{X}_k = \begin{pmatrix} x_{k-1} \\ y_{k-1} \\ \alpha_{k-1} \end{pmatrix} + \begin{pmatrix} \cos(\alpha_{k-1}) \\ \sin(\alpha_{k-1}) \\ 0 \end{pmatrix} u_{k-1} \tag{4.3}$$

Where u_{k-1} represents the step length, acting as the control input.

At this stage, the (EKF) equations are used to refine the pedestrian's position estimation through the PDR approach. The error covariance matrix P_k^- is computed using Eq (4.4):

$$P_k^- = F_k P_{k-1} F_k^T + Q_k \tag{4.4}$$

Where:

- F_k represents the Jacobian matrix,
- Q_k denotes the process noise covariance.

To improve the state estimate, the Kalman gain K_k is computed using Eq (4.5):

$$K_k = P_k^- H_k^T \left(H_k P_k^- H_k^T + R_k \right)^{-1} \tag{4.5}$$

With the Kalman gain, the state update equation is applied to obtain the corrected position estimate $\hat{X}_k$, as shown in Eq (4.6):

$$\hat{X}_k = \hat{X}_k^- + K_k \left(Z_k - H_k \hat{X}_k^- \right) \tag{4.6}$$

The updated error covariance matrix P_k is then computed using Eq (4.7):

$$P_k = (I_3 - K_k H_k)\, P_k^- \tag{4.7}$$

Where:

- $Z_k = \alpha_k$ represents the measurement input.
- $H_k = \begin{bmatrix} 0 & 0 & 1 \end{bmatrix}$ is the measurement matrix.
- R_k is the measurement noise covariance.
- I_3 is the 3×3 identity matrix.

This formulation ensures that position and heading estimates are continuously refined, enhancing the accuracy and robustness of the localization system.

4.3.3 Sensor Fusion Approach

To achieve highly accurate and robust localization, we propose a sensor fusion framework that integrates ORB-SLAM with the PDR-inertial system, utilizing data from both the smartphone's camera and IMU. This approach enhances position estimation accuracy by leveraging the complementary strengths of both methods.

A linear Kalman filter [166] was chosen as the sensor fusion technique due to its low computational complexity, making it more suitable for real-time applications by simplifying the problem to a linear estimation model.

The state transition function in the fusion framework, which is based on PDR localization, is formulated as follows: Given the 2D coordinates of a pedestrian at time t, denoted as X_k and the input vector $\Phi = \begin{bmatrix} P_{xt}^{pdr} & P_{yt}^{pdr} \end{bmatrix}^\top$, Where P_{xt}^{pdr} and P_{yt}^{pdr} represent the pedestrian's position along the X-axis and Y-axis, respectively, the state transition Eq (4.8) is expressed as:

$$X_t = F X_{t-1} + B\Phi_t + \upsilon \tag{4.8}$$

Where F and B are identity matrices, υ represents Gaussian noise in the motion model, Q is the process noise covariance matrix.

The observation function incorporates camera-based position data obtained from ORB-SLAM: $Z_t = \begin{bmatrix} P_{xt}^{orb} & P_{yt}^{orb} \end{bmatrix}$, the relationship between the observed position and the estimated state is given by Eq (4.9):

$$Z_t = H X_t + \omega \tag{4.9}$$

Where ω represents Gaussian noise in the ORB-SLAM output, R is the measurement noise covariance matrix,since this is a direct observation model, H is an identity matrix.

The Kalman filter-based fusion process consists of two main phases: prediction and update, ensuring real-time position correction.

4.3.3.1 Prediction Step

The prediction phase estimates the current state of the system based on the previous state and motion model. This step uses position estimates from the PDR-inertial system to forecast the device's next position.

The state prediction Eq (4.10) is:

$$X_{t|t-1} = FX_{t-1|t-1} + B\Phi_t \tag{4.10}$$

The error covariance matrix update is computed as Eq (4.11):

$$P_{t|t-1} = FP_{t-1|t-1}F^T + Q \tag{4.11}$$

These equations ensure that motion dynamics are accurately predicted, forming the basis for subsequent measurement updates.

4.3.3.2 Update Step

The update phase corrects the predicted state by incorporating real-time camera-based measurements from ORB-SLAM. This correction step ensures that the estimated position remains accurate by continuously integrating new observations.

The Kalman gain, which determines how much the observation influences the final estimate, is computed using Eq (4.12):

$$K_t = P_{t|t-1}H^T \left(HP_{t|t-1}H^T + R\right)^{-1} \tag{4.12}$$

The state estimate is then updated with Eq (4.13):

$$X_{t|t} = X_{t|t-1} + K_t \left(Z_t - HX_{t|t-1}\right) \tag{4.13}$$

Finally, the error covariance matrix is refined using Eq (4.14):

$$P_{t|t} = (I - K_t H)\, P_{t|t-1} \tag{4.14}$$

These prediction and update steps serve as the core of our fusion-based localization system, effectively integrating ORB-SLAM visual localization with PDR-inertial data. This combination significantly enhances the accuracy, stability, and robustness of indoor positioning.

4.4 Experimental Evaluation

This section presents the experimental validation of our smartphone-based indoor pedestrian localization system, which integrates ORB-SLAM with camera data and PDR-inertial sensor fusion. The primary goal is to evaluate the accuracy and effectiveness of the proposed fusion approach compared to using ORB-SLAM and PDR-inertial systems individually.

We provide a detailed description of the experimental setup, including the data collection process and the methodology used for performance analysis. Following this, we conduct a thorough evaluation of the results, offering an in-depth discussion on the system's performance and its practical implications.

4.4.1 Experimental Setup

The experiments were conducted on the third floor of the Faculty of Sciences and Technology at Mohamed El Bachir El Ibrahimi University of Bordj Bou Arreridj. This environment, illustrated in Figure 4.8 , features a complex indoor layout with a combination of corridors, classrooms, and open spaces, providing a challenging setting for indoor localization. Three distinct paths were selected for evaluation, each presenting unique difficulties such as signal obstructions, pedestrian movement, and environmental variations. The selected paths are depicted in Figure 4.9 and Figure 4.10 , include test environments in both small and large classrooms respectively . The lengths of these paths are as follows: Path 1 measures 16 m, Path 2 is 15 m, and Path 3 extends to 58 m.



Figure 4.8: Building in which experiments were carried out: Faculty ofSciences and Technology.



Figure 4.9: Test environment of Path 1 and 2: Small Classroom.

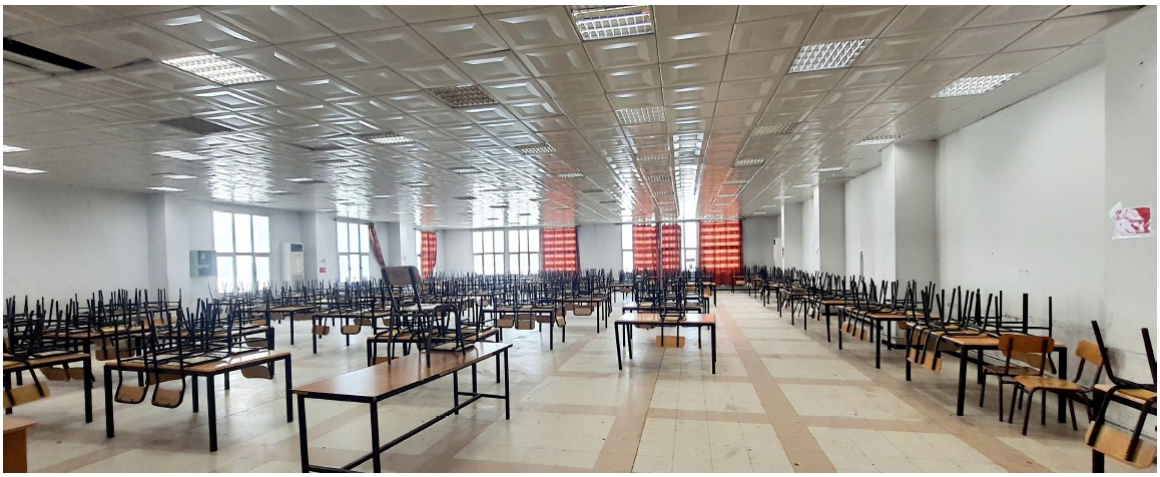


Figure 4.10: Test environment of Path 3: Big Classroom.

For system evaluation, a Samsung S9 Plus smartphone running Android 8.0 was utilized. The device is powered by a Snapdragon 845 (10 nm) processor and 6 GB of RAM, providing sufficient computational resources for the application. It features a 12 MP rear camera and inertial sensors, including an accelerometer and gyroscope, operating at a sampling rate of 100 Hz. Additionally, the magnetometer has a ±4800 μT range with high sensitivity. The performance characteristics of these sensors include an accelerometer noise density of 1818 μg/√Hz and a gyroscope noise density of 0.079 mdps/√Hz. These sensors are essential for feature extraction, motion tracking, and heading estimation, which are fundamental to the fusion-based localization approach.

To support the experiments, a custom Android application was developed specifically for data collection and localization processing. Figure 4.11 presents a screenshot of the Android-based navigation application interface.

During testing, volunteers aged 31 years, with an average height of 174 cm, walked naturally on flat ground, with the smartphone securely fastened to a body harness, as shown in Figure 4.12 . This setup ensured consistent device positioning and allowed for unrestricted movement during data collection, contributing to accurate and repeatable measurements.

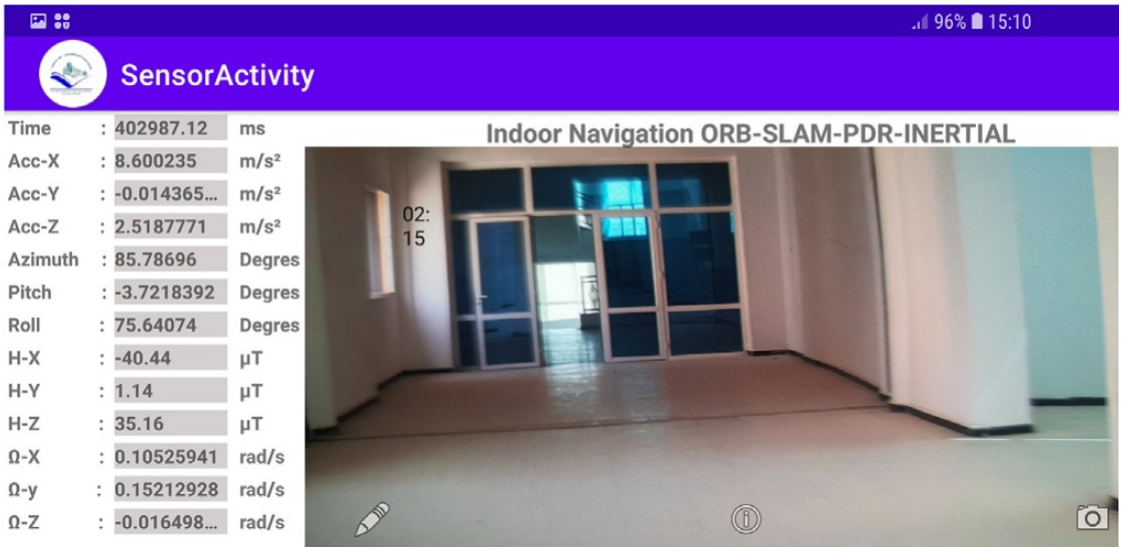


Figure 4.11: Screenshot of the developed android-based navigation application.



Figure 4.12: Our indoor navigation system.

4.4.2 Establishing a Reference Path

To achieve accurate and consistent linear motion in an indoor environment while using a smartphone secured to a body harness, a structured methodological approach was implemented. Since there is currently no highly reliable method to precisely define the correct path in such scenarios, a laser rangefinder was utilized to establish a reference point within the experimental area. Volunteers were instructed to walk smoothly along this designated reference path, with their movement time recorded to manually determine the true trajectory.

To validate the accuracy of the system, the estimated path derived from the Biscuit™ Programmable Wi-Fi 9-Axis Absolute Orientation Sensor IMU module was compared against the manually measured true path. The results demonstrated a strong alignment between the two paths, confirming the reliability and precision of the IMU module data. Consequently, for our experiments, the IMU-derived path was adopted as the true path, as depicted in Figure 4.13.



Figure 4.13: The IMU module used in our experiments to track motion and orientation.

The Biscuit™ IMU module offers high sensitivity and low noise density, making it well-suited for accurate motion sensing applications. The accelerometer exhibits a noise density of approximately 100 $\mu g/\sqrt{Hz}$, while the gyroscope provides a noise density of around $0.01°/s/\sqrt{Hz}$. These characteristics ensure the detection of even subtle movements with high precision. Additionally, the accelerometer supports an operational range of ±2 g to ±16 g, while the gyroscope operates within ±125°/s to ±2000°/s, allowing for accurate tracking across various motion scenarios.

This experimental setup was carefully designed to simulate real-world usage conditions, ensuring that the findings remain applicable to practical scenarios, particularly for visually impaired individuals. By adopting this methodological approach, we aimed to

provide robust and reliable insights into the performance and effectiveness of our localization system.

4.4.3 Methodology

The study's experimental methodology involved analyzing the collected data using our fusion approach, as well as standalone ORB-SLAM and PDR-inertial systems, for comparative purposes. The key evaluation metrics were the mean localization error, maximum error, minimum error, and standard deviation of the error. These metrics were selected to provide comprehensive insights into the accuracy, reliability, and consistency of the localization approaches under varying conditions.

4.5 Results and Discussion

In this study, three real-world experiments were conducted to evaluate the effectiveness of the proposed localization model. Through extensive testing to determine the optimal parameter settings, it was observed that R**=0.068** and Q**=0.1** produced the most favorable results.

The experiments involved comparing the performance of the fusion-based approach with two alternative methods: the independent ORB-SLAM algorithm and the standalone PDR-inertial system. To assess localization accuracy, the mean localization error was calculated for each experiment, followed by the computation of the overall average error across all trials. These values were then compared with those obtained using the standalone ORB-SLAM and PDR-based methods.

The numerical computation of the mean localization error (E) is defined in Eq 4.15 as follows:

$$E = \frac{1}{L}\sum_{i=1}^{L}\sqrt{(x_i^{\text{true}} - x_i^{\text{esti}})^2 + (y_i^{\text{true}} - y_i^{\text{esti}})^2} \tag{4.15}$$

Where $(x_i^{\text{true}},y_i^{\text{true}})$represent the actual user position, while $(x_i^{\text{esti}},y_i^{\text{true}})$ denote the estimated coordinates generated by the localization methods. The parameter L represents the total number of data samples used in the localization process.

A summary of the experimental findings is presented in Table 4.1, comparing the performance of the fusion-based system against the standalone ORB-SLAM and PDR-inertial methods across three different test paths. The results indicate that the proposed fusion method achieved a mean localization error of 0.62 m, which is significantly lower than the errors observed with ORB-SLAM (1.51 m) and PDR-inertial localization (1.69 m). Overall, the fusion approach reduced the mean localization error by 62%, demonstrating superior performance over standalone techniques.

Additionally, the fusion method exhibited enhanced reliability, as evidenced by a lower standard deviation of error, ensuring more consistent localization performance under various indoor conditions.

The localization trajectories for each test path, illustrated in Figure 4.14 , 4.15 , 4.16 and 4.17, provide a visual comparison between the fusion-based localization results and the ground-truth reference paths. These visualizations further substantiate the improved accuracy and tracking stability achieved by the fusion approach, particularly in complex indoor environments, where standalone systems often experience difficulties.

A notable observation was made in scenarios involving multiple loop closures, as shown in Figure 4.17. While the system successfully detected loop closure during the first iteration, it failed to recognize the loop closure in the second iteration. This limitation is likely due to environmental challenges, such as sparse or repetitive features, which hinder effective loop closure detection.

Experiments	**Localization methods**	**Mean error (m)**	**Max. error (m)**	**Min. error (m)**	**Std. deviation (m)**
Exper. #1	ORB-SLAM algorithm	0.938255100	2.80404887	0.029251563	1.062750271
	PDR-Inertial system	0.303460963	0.575961056	0.087825646	0.170984264
	Fusion approach	**0.159801039**	**0.563939341**	**0.014482902**	**0.125842789**
Exper. #2	ORB-SLAM algorithm	0.826808583	1.496574139	0.142776345	0.318247487
	PDR-Inertial system	1.555453434	2.481739785	0.223656452	0.639316378
	Fusion approach	**0.273021342**	**0.662225015**	**0.046179656**	**0.192085262**
Exper. #3	ORB-SLAM algorithm	2.799996656	4.807936522	1.061302272	1.067459971
	PDR-Inertial system	3.296757499	5.295363813	**0.023886788**	1.597182266
	Fusion approach	**1.451828896**	**2.564748079**	0.028349981	**0.743858503**

Table 4.1: Result of experiments of the fusion approach against PDR-Inertial and ORB-SLAM approaches.

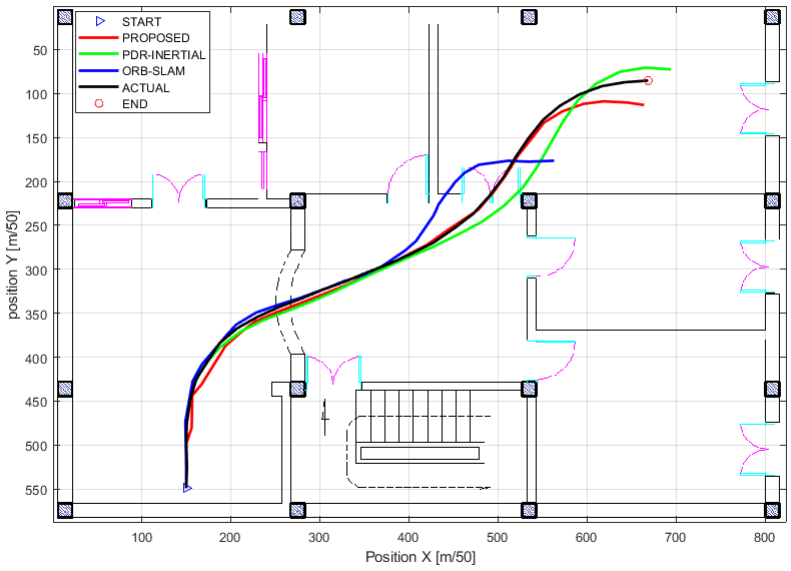


Figure 4.14: Localization trajectory for Path 1 (Small Classroom) inComparison to the ground-truth reference Path.

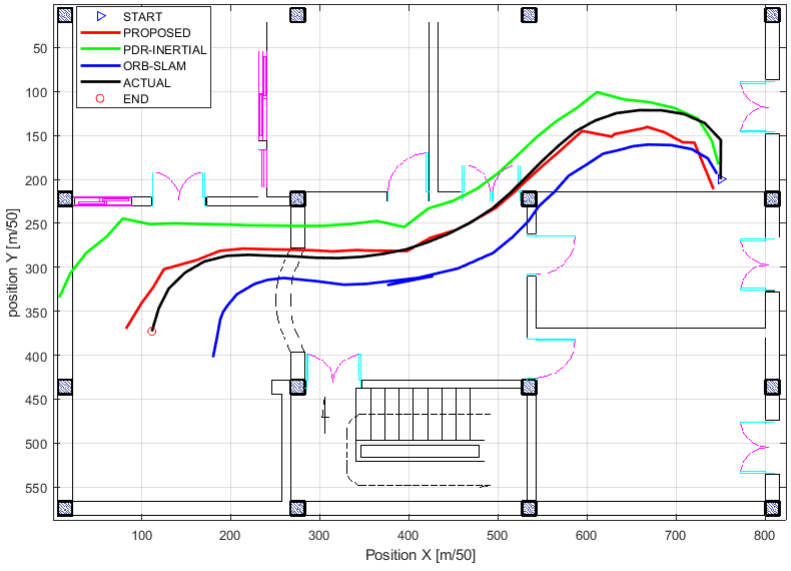


Figure 4.15: Localization trajectory for Path 2 (Small Classroom) inComparison to the ground-truth reference Path.

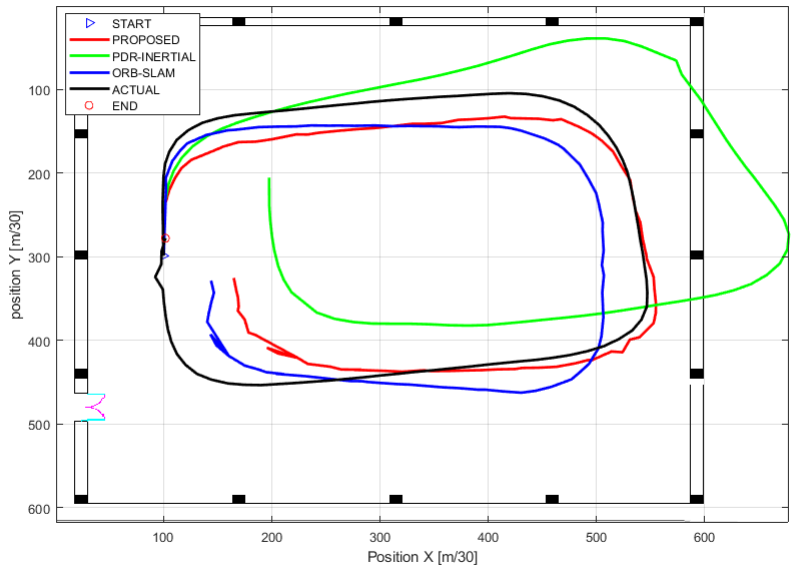


Figure 4.16: Localization trajectory for Path 3 (Big Classroom) in comparisonTo the ground-truth reference Path.

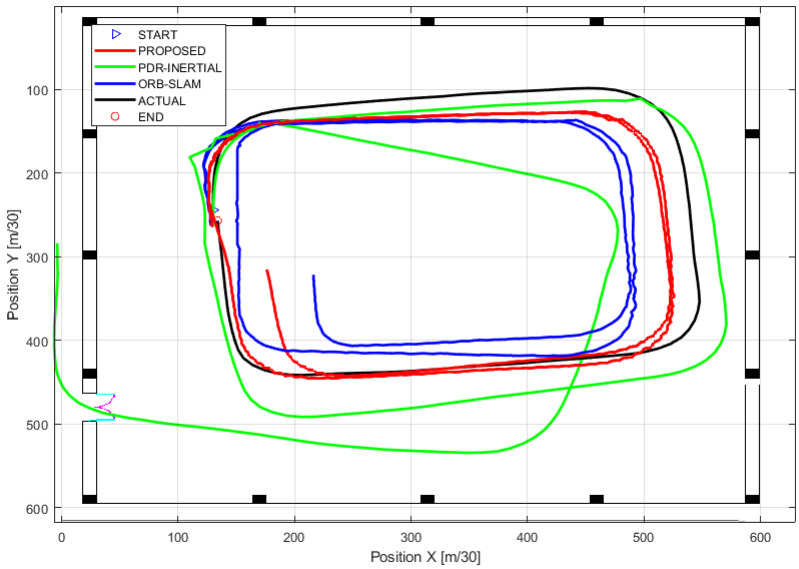


Figure 4.17: Localization trajectory for Path 4 multiple loops (Big Classroom) in comparisonTo the ground-truth reference Path.

Furthermore, Figure 4.18 (a)–(f) . present the localization error trends over time, along

with the Cumulative Distribution Function (CDF) of localization errors for each test path. These results emphasize the improved error distribution offered by the fusion approach, reinforcing its potential for real-time indoor localization applications.

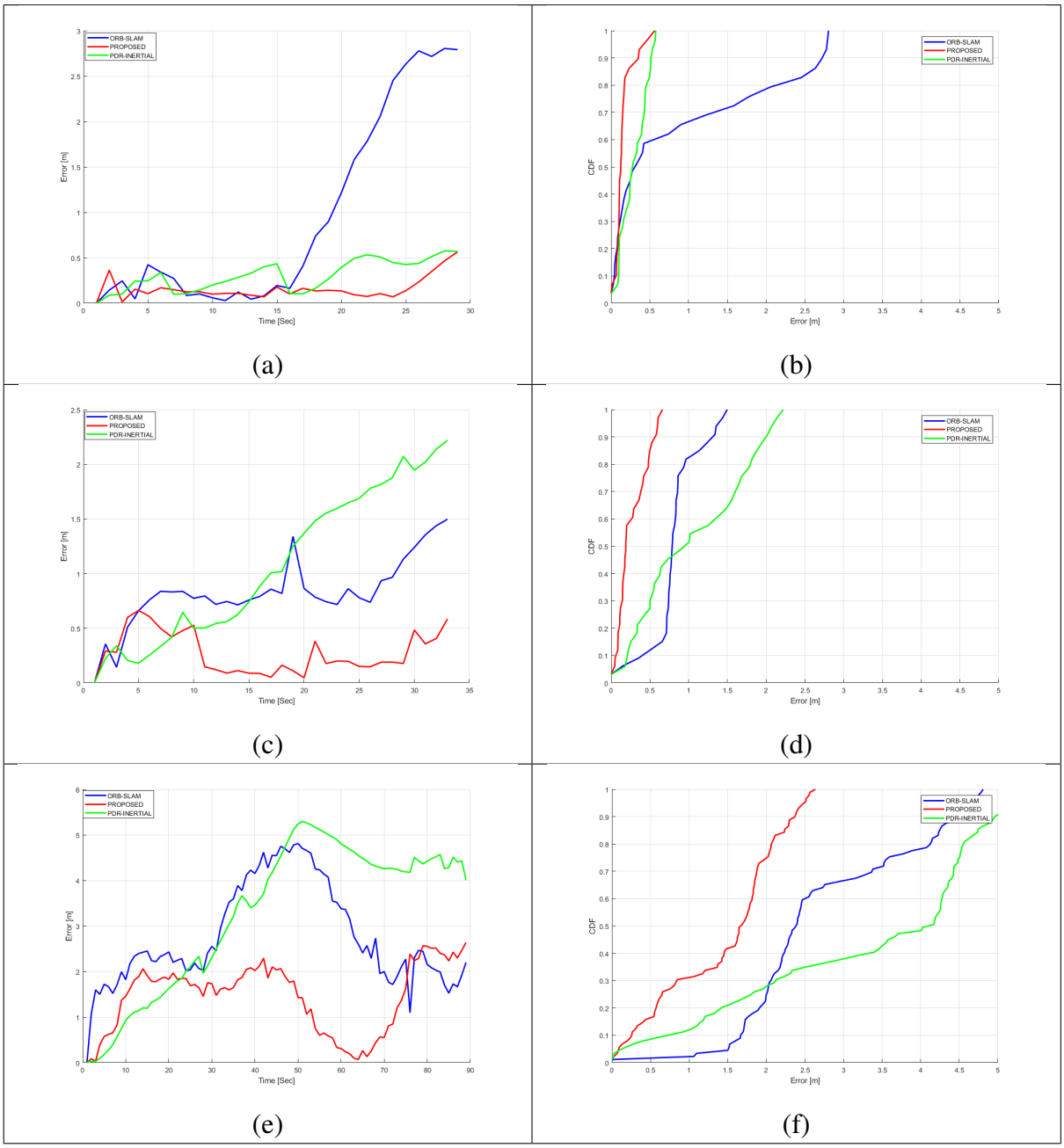


Figure 4.18: Localization error with respect to time and Cumulative Distribution Function (CDF) of Localization Errors, respectively: (a) and (b) for Path 1; (c) and (d) for Path 2; (e)and (f) for Path 3.

Beyond outperforming standalone ORB-SLAM and PDR-based methods, the proposed fusion system also demonstrated superior localization accuracy when compared with state-of-the-art techniques (e.g., [10, 12, 149]). Specifically, the CDF of localization errors reported in [10] (see Fig. 14 of [10]), which represents one of the most recent studies in the field, indicates that the proposed approach achieves a 59% reduction in mean localization error compared to existing methods. These findings highlight the suitability of the proposed system for real-time applications, particularly for assisting visually impaired individuals in navigating indoor environments with enhanced accuracy and reliability.

4.6 Conclusion

This study presents a practical and cost-effective solution for indoor pedestrian localization using a smartphone-based approach. The proposed method integrates two widely recognized techniques (PDR) and (SLAM), specifically ORB-SLAM within a unified sensor fusion framework. By leveraging camera data from ORB-SLAM and inertial sensor readings from PDR, the system employs a Kalman filter to perform backend fusion, ensuring high localization accuracy.

The developed localization system is tailored for indoor navigation, particularly to assist visually impaired individuals, enabling them to navigate independently and confidently using only their smartphones. Experimental results validate the effectiveness of the proposed approach, demonstrating a substantial reduction in mean localization error compared to standalone PDR and ORB-SLAM methods. Additionally, when benchmarked against state-of-the-art localization techniques, the proposed system achieves high accuracy, making it well-suited for real-time applications, especially for users with visual impairments.

Despite its promising performance, the smartphone-based ORB-SLAM and PDR fusion approach encounters certain challenges, including complex data synchronization, high computational requirements, and sensor calibration issues. Additionally, drift and localization errors may arise in challenging environments. Future research should focus on enhancing sensor fusion algorithms, implementing adaptive calibration techniques, improving power efficiency, and integrating additional sensors to further refine the system's performance and reliability.

Conclusion:

This doctoral thesis focuses on the development of a cost-effective, smartphone-based indoor navigation system tailored for visually impaired individuals. The study introduces two innovative approaches: a step-detection-controlled robotic guide dog and a smartphone-based localization system combining ORB-SLAM and (PDR). These solutions aim to provide accessible and reliable indoor navigation without relying on external infrastructure such as Wi-Fi beacons or (UWB) systems.

A comprehensive review of existing indoor localization techniques was conducted, encompassing vision-based, inertial, and hybrid positioning methods. This state-of-the-art analysis highlighted the strengths and limitations of each approach, providing a foundation for designing a more robust and adaptive localization system. Following this, a study of robotic guidance for visually impaired individuals was undertaken, exploring step-based control mechanisms and real-time obstacle avoidance strategies. The robotic guide dog was developed to synchronize its movement with the user's walking pace, leveraging smartphone accelerometers and Bluetooth-based communication for real-time haptic and text-based feedback.

To enhance the accuracy of smartphone-based localization, this research integrates ORB-SLAM and PDR to address the challenges of sensor drift and dynamic indoor environments. The fusion of visual and inertial data enables the system to maintain accurate positioning while mitigating the errors associated with standalone SLAM or PDR methods. Extensive experimental testing was performed in various indoor environments, evaluating the system's accuracy, responsiveness, and adaptability. Results demonstrated a significant improvement in localization precision, confirming the effectiveness of the proposed approach in real-world scenarios.

The efficacy of both the robotic guide system and the smartphone-based localization method was validated through a series of experiments and performance evaluations. These tests assessed step synchronization, obstacle avoidance, localization accuracy, and user adaptability. The results indicate that the proposed systems provide a reliable, infrastructure-free alternative for indoor navigation, with the potential to enhance mobility and independence for visually impaired users.

The findings from this research have been presented in scientific conferences and published in reputable journals, emphasizing the significance of these contributions in the fields of assistive technology and indoor localization. The successful implementation and validation of these systems demonstrate their potential as low-cost, scalable solutions for visually impaired navigation in complex indoor environments.

Future research directions include integrating AI-driven object recognition to improve scene understanding, optimizing SLAM algorithms for dynamic environments, and incor-

porating multimodal sensor fusion with additional technologies such as LiDAR or (UWB). Furthermore, user-centered long-term studies will be conducted to assess usability and accessibility in real-world conditions, ensuring that these solutions can be effectively deployed for enhanced mobility, safety, and independence.

Bibliography

[1] T. Liu, M. Wang, and T. Cheng, "Through-wall localization based on exponential moving average and distance decay elliptic model," in *2023 International Conference on Sensing, Measurement & Data Analytics in the era of Artificial Intelligence (ICSMD)*. IEEE, 2023, pp. 1–6.

[2] X. Huang, S. Guo, Y. Wu, and Y. Yang, "A fine-grained indoor fingerprinting localization based on magnetic field strength and channel state information," *Pervasive and mobile computing*, vol. 41, pp. 150–165, 2017.

[3] A. Simončič, T. Javornik, A. Sešek, and A. Hrovat, "Direction of arrival estimation for ble: Antenna array design and evaluation," *AEU-International Journal of Electronics and Communications*, vol. 168, p. 154722, 2023.

[4] J. Chen, S. Song, and H. Yu, "An indoor multi-source fusion positioning approach based on pdr/mm/wifi," *AEU-International Journal of Electronics and Communications*, vol. 135, p. 153733, 2021.

[5] G. Zhao, X. Wang, H. Zhao, and Z. Jiang, "An improved pedestrian dead reckoning algorithm based on smartphone built-in mems sensors," *AEU-International Journal of Electronics and Communications*, vol. 168, p. 154674, 2023.

[6] A. Correa, M. Barcelo, A. Morell, and J. L. Vicario, "A review of pedestrian indoor positioning systems for mass market applications," *Sensors*, vol. 17, no. 8, p. 1927, 2017.

[7] I. Apostolopoulos, N. Fallah, E. Folmer, and K. E. Bekris, "Integrated online localization and navigation for people with visual impairments using smart phones," *ACM Transactions on Interactive Intelligent Systems (TiiS)*, vol. 3, no. 4, pp. 1–28, 2014.

[8] D. Khan, Z. Cheng, H. Uchiyama, S. Ali, M. Asshad, and K. Kiyokawa, "Recent advances in vision-based indoor navigation: A systematic literature review," *Computers & Graphics*, vol. 104, pp. 24–45, 2022.

[9] Q. Wang, K. Zhang, K. Zhao, and M. Liao, "Smart seeing eye dog wheeled assistive robotics," in *2021 3rd International Symposium on Robotics & Intelligent Manufacturing Technology (ISRIMT)*. IEEE, 2021, pp. 104–108.

[10] D. Yan, C. Shi, T. Li, H. Jiang, M. Xia, Q. Guo, and Y. Li, "Ps-vins: A visual–inertial slam system with pedestrian gait and structural constraints using smartphone sensors," *IEEE Sensors Journal*, vol. 24, no. 5, pp. 6777–6791, 2024.

[11] M. Zhong, Y. You, S. Zhou, and X. Xu, "A robust visual–inertial slam in complex indoor environments," *IEEE Sensors Journal*, vol. 23, no. 17, pp. 19 986–19 994, 2023.

[12] Y. Dong, D. Yan, T. Li, M. Xia, and C. Shi, "Pedestrian gait information aided visual inertial slam for indoor positioning using handheld smartphones," *IEEE Sensors Journal*, vol. 22, no. 20, pp. 19 845–19 857, 2022.

[13] R. Mur-Artal and J. D. Tardós, "Visual-inertial monocular slam with map reuse," *IEEE Robotics and Automation Letters*, vol. 2, no. 2, pp. 796–803, 2017.

[14] A. Hamadi and A. Latoui, "Step-detection-controlled robot dog guide for visually impaired pedestrians," in *2024 International Conference on Advances in Electrical and Communication Technologies (ICAECOT)*. IEEE, 2024, pp. 1–5.

[15] R. Mur-Artal, J. M. M. Montiel, and J. D. Tardos, "Orb-slam: A versatile and accurate monocular slam system," *IEEE transactions on robotics*, vol. 31, no. 5, pp. 1147–1163, 2015.

[16] A. Hamadi and A. Latoui, "An accurate smartphone-based indoor pedestrian localization system using orb-slam camera and pdr inertial sensors fusion approach," *Measurement*, vol. 240, p. 115642, 2025.

[17] D. González, J. Pérez, V. Milanés, and F. Nashashibi, "A review of motion planning techniques for automated vehicles," *IEEE Transactions on intelligent transportation systems*, vol. 17, no. 4, pp. 1135–1145, 2015.

[18] A. Ceder, *Public transit planning and operation: Modeling, practice and behavior*. CRC press, 2016.

[19] L. T. Ross, S. W. Fardo, and M. F. Walach, *Industrial robotics fundamentals: Theory and applications*. Goodheart-Willcox Co., 2017.

[20] M. S. Grewal, L. R. Weill, and A. P. Andrews, *Global positioning systems, inertial navigation, and integration*. John Wiley & Sons, 2007.

[21] O. Wendt, R. W. Quist, and L. L. Lloyd, *Assistive technology: Principles and applications for communication disorders and special education*. Brill, 2011, vol. 4.

[22] S. Thrun, "Probabilistic robotics," *Communications of the ACM*, vol. 45, no. 3, pp. 52–57, 2002.

[23] N. B. Priyantha, "The cricket indoor location system," Ph.D. dissertation, Massachusetts Institute of Technology, 2005.

[24] A. P. Junior, L. E. Díez, A. Bahillo, and O. S. Eyobu, "Remote pedestrian localization systems for resource-constrained environments: a systematic review," *IEEE Access*, vol. 11, pp. 36 865–36 889, 2023.

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

[26] S. Zekavat, R. M. Buehrer, G. D. Durgin, L. Lovisolo, Z. Wang, S. T. Goh, and A. Ghasemi, "An overview on position location: Past, present, future," *International Journal of Wireless Information Networks*, vol. 28, pp. 45–76, 2021.

[27] F. Zangenehnejad and Y. Gao, "Gnss smartphones positioning: Advances, challenges, opportunities, and future perspectives," *Satellite navigation*, vol. 2, pp. 1–23, 2021.

[28] S. Monica and F. Bergenti, "Hybrid indoor localization using wifi and uwb technologies," *Electronics*, vol. 8, no. 3, p. 334, 2019.

[29] E. D. Kaplan and C. Hegarty, *Understanding GPS/GNSS: principles and applications*. Artech house, 2017.

[30] P. Flores and P. Flores, "Global and local coordinates," *Concepts and Formulations for Spatial Multibody Dynamics*, pp. 11–14, 2015.

[31] F. Zafari, A. Gkelias, and K. K. Leung, "A survey of indoor localization systems and technologies," *IEEE Communications Surveys & Tutorials*, vol. 21, no. 3, pp. 2568–2599, 2019.

[32] H. Liu, H. Darabi, P. Banerjee, and J. Liu, "Survey of wireless indoor positioning techniques and systems," *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)*, vol. 37, no. 6, pp. 1067–1080, 2007.

[33] J. A. Fangmeyer JR, C. V. Rosales, D. M. Rodríguez, and R. F. B. Pinero, "Evolution of indoor positioning technologies: A survey," 2017.

[34] C. Isaia and M. P. Michaelides, "A review of wireless positioning techniques and technologies: From smart sensors to 6g," *Signals*, vol. 4, no. 1, pp. 90–136, 2023.

[35] J. Levinson, M. Montemerlo, and S. Thrun, "Map-based precision vehicle localization in urban environments." in *Robotics: science and systems*, vol. 4, no. Citeseer. Atlanta, GA, USA, 2007, pp. 121–128.

[36] J. Fayyad, M. A. Jaradat, D. Gruyer, and H. Najjaran, "Deep learning sensor fusion for autonomous vehicle perception and localization: A review," *Sensors*, vol. 20, no. 15, p. 4220, 2020.

[37] D. J. Yeong, G. Velasco-Hernandez, J. Barry, and J. Walsh, "Sensor and sensor fusion technology in autonomous vehicles: A review," *Sensors*, vol. 21, no. 6, p. 2140, 2021.

[38] M. Haloi and D. B. Jayagopi, "A robust lane detection and departure warning system," in *2015 IEEE Intelligent Vehicles Symposium (IV)*. IEEE, 2015, pp. 126–131.

[39] M. Y. Arafat, M. M. Alam, and S. Moh, "Vision-based navigation techniques for unmanned aerial vehicles: Review and challenges," *Drones*, vol. 7, no. 2, p. 89, 2023.

[40] M. S. M. Moreira, D. K. D. Villa, and M. Sarcinelli-Filho, "Controlling a virtual structure involving a uav and a ugv for warehouse inventory," *Journal of Intelligent & Robotic Systems*, vol. 110, no. 3, p. 121, 2024.

[41] A. Gupta and X. Fernando, "Simultaneous localization and mapping (slam) and data fusion in unmanned aerial vehicles: Recent advances and challenges," *Drones*, vol. 6, no. 4, p. 85, 2022.

[42] H.-W. Choi, H.-J. Kim, S.-K. Kim, and W. S. Na, "An overview of drone applications in the construction industry," *Drones*, vol. 7, no. 8, p. 515, 2023.

[43] A. Soussi, E. Zero, R. Sacile, D. Trinchero, and M. Fossa, "Smart sensors and smart data for precision agriculture: A review," *Sensors*, vol. 24, no. 8, p. 2647, 2024.

[44] F. Svanström, F. Alonso-Fernandez, and C. Englund, "Drone detection and tracking in real-time by fusion of different sensing modalities," *Drones*, vol. 6, no. 11, p. 317, 2022.

[45] G. I. Okolo, T. Althobaiti, and N. Ramzan, "Assistive systems for visually impaired persons: challenges and opportunities for navigation assistance," *Sensors*, vol. 24, no. 11, p. 3572, 2024.

[46] P. Slade, A. Tambe, and M. J. Kochenderfer, "Multimodal sensing and intuitive steering assistance improve navigation and mobility for people with impaired vision. science robotics 6, 59 (2021), eabg6594," 2021.

[47] H. Obeidat, W. Shuaieb, O. Obeidat, and R. Abd-Alhameed, "A review of indoor localization techniques and wireless technologies," *Wireless Personal Communications*, vol. 119, pp. 289–327, 2021.

[48] C. Huang, F. Zhang, Z. Xu, and J. Wei, "Adaptive pedestrian stride estimation for localization: From multi-gait perspective," *Sensors*, vol. 22, no. 8, p. 2840, 2022.

[49] B. Abdulrahman and Z. Zhu, "Real-time pedestrian pose estimation, tracking and localization for social distancing," *Machine vision and applications*, vol. 34, no. 1, p. 8, 2023.

[50] N. Ward, "Understanding gpsâprinciples and applications. elliott d. kaplan (editor).£ 75. isbn: 0-89006-793-7. artech house publishers, boston & london. 1996." *The Journal of Navigation*, vol. 50, no. 1, pp. 151–152, 1997.

[51] Y. J. Guo, *Advances in mobile radio access networks*. Artech House, 2004.

[52] R. F. Brena, J. P. García-Vázquez, C. E. Galván-Tejada, D. Muñoz-Rodriguez, C. Vargas-Rosales, and J. Fangmeyer Jr, "Evolution of indoor positioning technologies: A survey," *Journal of Sensors*, vol. 2017, no. 1, p. 2630413, 2017.

[53] O. Hashem, K. A. Harras, and M. Youssef, "Accurate indoor positioning using ieee 802.11 mc round trip time," *Pervasive and Mobile Computing*, vol. 75, p. 101416, 2021.

[54] V. Garg and M. Jhamb, "A review of wireless sensor network on localization techniques," *Int. J. Eng. Trends Technol*, vol. 4, no. 4, pp. 1049–1053, 2013.

[55] J. Luo, L. Fan, and H. Li, "Indoor positioning systems based on visible light communication: State of the art," *IEEE Communications Surveys & Tutorials*, vol. 19, no. 4, pp. 2871–2893, 2017.

[56] M. Si, Y. Wang, S. Xu, M. Sun, and H. Cao, "A wi-fi ftm-based indoor positioning method with los/nlos identification," *Applied Sciences*, vol. 10, no. 3, p. 956, 2020.

[57] Y. Zhang and L. Duan, "A phase-difference-of-arrival assisted ultra-wideband positioning method for elderly care," *Measurement*, vol. 170, p. 108689, 2021.

[58] S. Kawakami and T. Ohtsuki, "Localization using iterative angle of arrival method sharing snapshots of coherent subarrays," *EURASIP Journal on Advances in Signal Processing*, vol. 2011, pp. 1–7, 2011.

[59] H. L. Bertoni, *Radio propagation for modern wireless systems*. Pearson Education, 1999.

[60] T. S. Rappaport, *Wireless communications: principles and practice*. Cambridge University Press, 2024.

[61] R. Chatterjee, *Antenna theory and practice*. New Age International, 1996.

[62] A. A. Khudhair, S. Q. Jabbar, M. Q. Sulttan, and D. Wang, "Wireless indoor localization systems and techniques: survey and comparative study," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 3, no. 2, pp. 392–409, 2016.

[63] F. Zafari, I. Papapanagiotou, M. Devetsikiotis, and T. Hacker, "An ibeacon based proximity and indoor localization system," *arXiv preprint arXiv:1703.07876*, 2017.

[64] A. Norrdine, "An algebraic solution to the multilateration problem," in *Proceedings of the 15th international conference on indoor positioning and indoor navigation, Sydney, Australia*, vol. 1315, 2012.

[65] D. Burghal, A. T. Ravi, V. Rao, A. A. Alghafis, and A. F. Molisch, "A comprehensive survey of machine learning based localization with wireless signals," *arXiv preprint arXiv:2012.11171*, 2020.

[66] A. Nessa, B. Adhikari, F. Hussain, and X. N. Fernando, "A survey of machine learning for indoor positioning," *IEEE access*, vol. 8, pp. 214 945–214 965, 2020.

[67] I. Ashraf, S. Hur, and Y. Park, "Smartphone sensor based indoor positioning: Current status, opportunities, and future challenges," *Electronics*, vol. 9, no. 6, p. 891, 2020.

[68] R. Harle, "A survey of indoor inertial positioning systems for pedestrians," *IEEE Communications Surveys & Tutorials*, vol. 15, no. 3, pp. 1281–1293, 2013.

[69] J.-O. Nilsson, A. K. Gupta, and P. Händel, "Foot-mounted inertial navigation made easy," in *2014 International Conference on Indoor Positioning and Indoor Navigation (IPIN)*. IEEE, 2014, pp. 24–29.

[70] S. Huang, K. Zhao, Z. Zheng, W. Ji, T. Li, and X. Liao, "An optimized fingerprinting-based indoor positioning with kalman filter and universal kriging for 5g internet of things," *Wireless Communications and Mobile Computing*, vol. 2021, no. 1, p. 9936706, 2021.

[71] C.-Y. Yang, H. Samani, Z. Tang, and C. Li, "Implementation of extended kalman filter for localization of ambulance robot," *International Journal of Intelligent Robotics and Applications*, vol. 8, no. 4, pp. 960–973, 2024.

[72] J. Engström, Å. Jevinger, C. M. Olsson, and J. A. Persson, "Some design considerations in passive indoor positioning systems," *Sensors*, vol. 23, no. 12, p. 5684, 2023.

[73] G. Chen, X. Meng, Y. Wang, Y. Zhang, P. Tian, and H. Yang, "Integrated wifi/pdr/smartphone using an unscented kalman filter algorithm for 3d indoor localization," *Sensors*, vol. 15, no. 9, pp. 24 595–24 614, 2015.

[74] D. Luo, Y. Huang, X. Huang, M. Miao, and X. Gao, "W-vslam: A visual mapping algorithm for indoor inspection robots," *Sensors*, vol. 24, no. 17, p. 5662, 2024.

[75] F. Potorti, S. Park, A. Crivello, F. Palumbo, M. Girolami, P. Barsocchi, S. Lee, J. Torres-Sospedra, A. R. J. Ruiz, A. Perez-Navarro *et al.*, "The ipin 2019 indoor localisation competitionâdescription and results," *IEEE access*, vol. 8, pp. 206 674–206 718, 2020.

[76] S. Kaiser, "Successive collaborative slam: Towards reliable inertial pedestrian navigation," *Information*, vol. 11, no. 10, p. 464, 2020.

[77] P. Bahl and V. N. Padmanabhan, "Radar: An in-building rf-based user location and tracking system," in *Proceedings IEEE INFOCOM 2000. Conference on computer communications. Nineteenth annual joint conference of the IEEE computer and communications societies (Cat. No. 00CH37064)*, vol. 2. Ieee, 2000, pp. 775–784.

[78] P. Castro, P. Chiu, T. Kremenek, and R. Muntz, "A probabilistic room location service for wireless networked environments," in *Ubicomp 2001: Ubiquitous Computing: International Conference Atlanta Georgia, USA, September 30–October 2, 2001 Proceedings 3*. Springer, 2001, pp. 18–34.

[79] M. Youssef and A. Agrawala, "The horus wlan location determination system," in *Proceedings of the 3rd international conference on Mobile systems, applications, and services*, 2005, pp. 205–218.

[80] Y. Gu, A. Lo, and I. Niemegeers, "A survey of indoor positioning systems for wireless personal networks," *IEEE Communications surveys & tutorials*, vol. 11, no. 1, pp. 13–32, 2009.

[81] A. M. Hossain and W.-S. Soh, "A comprehensive study of bluetooth signal parameters for localization," in *2007 IEEE 18th International Symposium on Personal, Indoor and Mobile Radio Communications*. IEEE, 2007, pp. 1–5.

[82] X.-Y. Lin, T.-W. Ho, C.-C. Fang, Z.-S. Yen, B.-J. Yang, and F. Lai, "A mobile indoor positioning system based on ibeacon technology," in *2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*. IEEE, 2015, pp. 4970–4973.

[83] M. Choi, W.-K. Park, and I. Lee, "Smart office energy management system using bluetooth low energy based beacons and a mobile app," in *2015 IEEE International Conference on Consumer Electronics (ICCE)*. IEEE, 2015, pp. 501–502.

[84] A. Fujihara and T. Yanagizawa, "Proposing an extended ibeacon system for indoor route guidance," in *2015 international conference on intelligent networking and collaborative systems*. IEEE, 2015, pp. 31–37.

[85] F. Subhan, H. Hasbullah, A. Rozyyev, and S. T. Bakhsh, "Indoor positioning in bluetooth networks using fingerprinting and lateration approach," in *2011 International Conference on Information Science and Applications*. IEEE, 2011, pp. 1–9.

[86] T. A. Alhmiedat and S.-H. Yang, "A zigbee-based mobile tracking system through wireless sensor networks," *International Journal of Advanced Mechatronic Systems*, vol. 1, no. 1, pp. 63–70, 2008.

[87] A. Wheeler, "Commercial applications of wireless sensor networks using zigbee," *IEEE communications magazine*, vol. 45, no. 4, pp. 70–77, 2007.

[88] S.-H. Fang, C.-H. Wang, T.-Y. Huang, C.-H. Yang, and Y.-S. Chen, "An enhanced zigbee indoor positioning system with an ensemble approach," *IEEE Communications Letters*, vol. 16, no. 4, pp. 564–567, 2012.

[89] R. Weinstein, "Rfid: a technical overview and its application to the enterprise," *IT professional*, vol. 7, no. 3, pp. 27–33, 2005.

[90] K. Ahsan, H. Shah, and P. Kingston, "Rfid applications: An introductory and exploratory study," *arXiv preprint arXiv:1002.1179*, 2010.

[91] Y. C. Lau, A. Patil, L. Ni, and Y. Liu, "Landmarc: indoor location sensing using active rfid," *Wireless networks*, vol. 10, no. 6, pp. 701–710, 2004.

[92] U. Biader Ceipidor, C. Medaglia, A. Serbanati, G. Azzalin, M. Barboni, F. Rizzo, and M. Sironi, "Sesamonet: an rfid-based economically viable navigation system for the visually impaired," *International Journal of RF Technologies: Research and Applications*, vol. 1, no. 3, pp. 214–224, 2009.

[93] Z. Farid, R. Nordin, and M. Ismail, "Recent advances in wireless indoor localization techniques and system," *Journal of Computer Networks and Communications*, vol. 2013, no. 1, p. 185138, 2013.

[94] A. R. J. Ruiz and F. S. Granja, "Comparing ubisense, bespoon, and decawave uwb location systems: Indoor performance analysis," *IEEE Transactions on instrumentation and Measurement*, vol. 66, no. 8, pp. 2106–2117, 2017.

[95] B. Yan and L. Xiaochun, "Research on uwb indoor positioning based on tdoa technique," in *2009 9th International Conference on Electronic Measurement & Instruments*. IEEE, 2009, pp. 1–167.

[96] R. Want, A. Hopper, V. Falcao, and J. Gibbons, "The active badge location system," *ACM Transactions on Information Systems (TOIS)*, vol. 10, no. 1, pp. 91–102, 1992.

[97] E. M. Gorostiza, J. L. Lázaro Galilea, F. J. Meca Meca, D. Salido Monzú, F. Espinosa Zapata, and L. Pallarés Puerto, "Infrared sensor system for mobile-robot positioning in intelligent spaces," *Sensors*, vol. 11, no. 5, pp. 5416–5438, 2011.

[98] A. Rogalski, "Infrared detectors: an overview," *Infrared physics & technology*, vol. 43, no. 3-5, pp. 187–210, 2002.

[99] K. Y. Yi, D. Y. Kim, and K. M. Yi, "Development of a localization system based on vlc technique for an indoor environment," *Journal of Electrical Engineering and Technology*, vol. 10, no. 1, pp. 436–442, 2015.

[100] T. Komine and M. Nakagawa, "Fundamental analysis for visible-light communication system using led lights," *IEEE transactions on Consumer Electronics*, vol. 50, no. 1, pp. 100–107, 2004.

[101] N. Kumar, N. Lourenco, M. Spiez, and R. L. Aguiar, "Visible light communication systems conception and vidas," *IETE Technical Review*, vol. 25, no. 6, pp. 359–367, 2008.

[102] W. Zhang, M. S. Chowdhury, and M. Kavehrad, "Asynchronous indoor positioning system based on visible light communications," *Optical Engineering*, vol. 53, no. 4, pp. 045 105–045 105, 2014.

[103] B. M. Al-Hadithi and C. Pastor, "Cost-effective localization of mobile robots using ultrasound beacons and differential time-of-flight measurement," *Applied Sciences*, vol. 14, no. 17, p. 7597, 2024.

[104] D. Gualda, J. Ureña, J. C. García, E. García, and J. Alcala, "Simultaneous calibration and navigation (scan) of multiple ultrasonic local positioning systems," *Information Fusion*, vol. 45, pp. 53–65, 2019.

[105] E. Dalmas, F. Danneville, F. Elbahhar, M. Bocquet, and C. Loyez, "A review of neuromorphic sound source localization and echolocation-based navigation systems," *Electronics*, vol. 13, no. 24, p. 4858, 2024.

[106] M. Bakouri, N. Alyami, A. Alassaf, M. Waly, T. Alqahtani, I. AlMohimeed, A. Alqahtani, M. Samsuzzaman, H. F. Ismail, and Y. Alharbi, "Sound-based localization using lstm networks for visually impaired navigation," *Sensors*, vol. 23, no. 8, p. 4033, 2023.

[107] S. Beeby, *MEMS mechanical sensors*. Artech House, 2004.

[108] C. Jekeli, *Inertial navigation systems with geodetic applications*. Walter de Gruyter GmbH & Co KG, 2023.

[109] A. Poulose, J. Kim, and D. S. Han, "A sensor fusion framework for indoor localization using smartphone sensors and wi-fi rssi measurements," *Applied Sciences*, vol. 9, no. 20, p. 4379, 2019.

[110] P. Huynh and M. Yoo, "Vlc-based positioning system for an indoor environment using an image sensor and an accelerometer sensor," *Sensors*, vol. 16, no. 6, p. 783, 2016.

[111] K. Choutri, M. Lagha, S. Meshoul, H. Shaiba, A. Chegrani, and M. Yahiaoui, "Vision-based uav detection and localization to indoor positioning system," *Sensors*, vol. 24, no. 13, p. 4121, 2024.

[112] R. K. Crane, *Propagation handbook for wireless communication system design*. CRC press, 2003.

[113] E. L. Christensen and G. Mogensen, "Experimental investigation of line-of-sight propagation at 13.5–15.0 ghz," *Radio and Electronic Engineer*, vol. 49, no. 3, pp. 127–140, 1979.

[114] A. Poulose, O. S. Eyobu, and D. S. Han, "An indoor position-estimation algorithm using smartphone imu sensor data," *Ieee Access*, vol. 7, pp. 11 165–11 177, 2019.

[115] H. Soganci, S. Gezici, and H. V. Poor, "Accurate positioning in ultra-wideband systems," *IEEE Wireless Communications*, vol. 18, no. 2, pp. 19–27, 2011.

[116] R. Wang, G. Niu, Q. Cao, C. S. Chen, and S.-W. Ho, "A survey of visible-light-communication-based indoor positioning systems," *Sensors*, vol. 24, no. 16, p. 5197, 2024.

[117] C. Cadena, L. Carlone, H. Carrillo, Y. Latif, D. Scaramuzza, J. Neira, I. Reid, and J. J. Leonard, "Past, present, and future of simultaneous localization and mapping: Toward the robust-perception age," *IEEE Transactions on robotics*, vol. 32, no. 6, pp. 1309–1332, 2016.

[118] R. Faragher and R. Harle, "Location fingerprinting with bluetooth low energy beacons," *IEEE journal on Selected Areas in Communications*, vol. 33, no. 11, pp. 2418–2428, 2015.

[119] World Health Organization, "Global Vision Impairment and Blindness," 2023, [Online; accessed 26-April-2024]. [Online]. Available: https://www.who.int/news-room/fact-sheets/detail/blindness-and-visual-impairment

[120] E. Cardillo and A. Caddemi, "Insight on electronic travel aids for visually impaired people: A review on the electromagnetic technology," *Electronics*, vol. 8, no. 11, p. 1281, 2019.

[121] T. Kiuru, M. Metso, M. Utriainen, K. Metsävainio, H.-M. Jauhonen, R. Rajala, R. Savenius, M. Ström, T.-N. Jylhä, R. Juntunen *et al.*, "Assistive device for orientation and mobility of the visually impaired based on millimeter wave radar technologyâclinical investigation results," *Cogent Engineering*, vol. 5, no. 1, p. 1450322, 2018.

[122] R. Agarwal, N. Ladha, M. Agarwal, K. K. Majee, A. Das, S. Kumar, S. K. Rai, A. K. Singh, S. Nayak, S. Dey *et al.*, "Low cost ultrasonic smart glasses for blind," in *2017 8th IEEE Annual Information Technology, Electronics and Mobile Communication Conference (IEMCON)*. IEEE, 2017, pp. 210–213.

[123] J. Borenstein and I. Ulrich, "The guidecane-a computerized travel aid for the active guidance of blind pedestrians," in *Proceedings of International Conference on Robotics and Automation*, vol. 2. IEEE, 1997, pp. 1283–1288.

[124] D. Sato, U. Oh, K. Naito, H. Takagi, K. Kitani, and C. Asakawa, "Navcog3: An evaluation of a smartphone-based blind indoor navigation assistant with semantic features in a large-scale environment," in *Proceedings of the 19th International ACM SIGACCESS Conference on Computers and Accessibility*, 2017, pp. 270–279.

[125] R. Shilkrot, "Digital digits: designing assistive finger augmentation devices," Ph.D. dissertation, Massachusetts Institute of Technology, 2015.

[126] V. Kulyukin, C. Gharpure, J. Nicholson, and S. Pavithran, "Rfid in robot-assisted indoor navigation for the visually impaired," in *2004 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)(IEEE Cat. No. 04CH37566)*, vol. 2. IEEE, 2004, pp. 1979–1984.

[127] A. Cruces, A. Jerez, J. P. Bandera, and A. Bandera, "Socially assistive robots in smart environments to attend elderly peopleâa survey," *Applied Sciences*, vol. 14, no. 12, p. 5287, 2024.

[128] NoorCam, "Noorcam myeye," 2025, accessed: Feb. 14, 2025. [Online]. Available: https://www.noorcam.com/en-ae/noorcam-myeye

[129] O. Ozioko and R. Dahiya, "Smart tactile gloves for haptic interaction, communication, and rehabilitation," *Advanced Intelligent Systems*, vol. 4, no. 2, p. 2100091, 2022.

[130] D. R. Bruno, M. H. de Assis, and F. S. Osório, "Development of a mobile robot: Robotic guide dog for aid of visual disabilities in urban environments," in *2019 Latin American Robotics Symposium (LARS), 2019 Brazilian Symposium on*

Robotics (SBR) and 2019 Workshop on Robotics in Education (WRE). IEEE, 2019, pp. 104–108.

[131] Y. Wei and M. Lee, "A guide-dog robot system research for the visually impaired," in *2014 IEEE International Conference on Industrial Technology (ICIT)*. IEEE, 2014, pp. 800–805.

[132] A. Xiao, W. Tong, L. Yang, J. Zeng, Z. Li, and K. Sreenath, "Robotic guide dog: Leading a human with leash-guided hybrid physical interaction," in *2021 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2021, pp. 11 470–11 476.

[133] S. Woo, J. Shin, Y. H. Lee, Y. H. Lee, H. Lee, H. Kang, H. R. Choi, and H. Moon, "Stair-mapping with point-cloud data and stair-modeling for quadruped robot," in *2019 16th international conference on ubiquitous robots (UR)*. IEEE, 2019, pp. 81–86.

[134] T. J. Son, A. H. A. Hassan, and M. H. Jairan, "Optimized robot mapping and obstacle avoidance using stereo vision," in *2021 IEEE 11th IEEE Symposium on Computer Applications & Industrial Electronics (ISCAIE)*. IEEE, 2021, pp. 279–284.

[135] J. Sparbert, J. Kümpel, and E. P. Hofer, "Motion control of a mobile robot with adaption to the environment," in *2001 European Control Conference (ECC)*. IEEE, 2001, pp. 1145–1150.

[136] X. Liu, Z. Liu, F. Zan, W. Chen, and X. Zhang, "Research on path planning method of intelligent robot based on a* algorithm," in *2022 IEEE 5th International Conference on Information Systems and Computer Aided Education (ICISCAE)*. IEEE, 2022, pp. 536–539.

[137] J. Guerreiro, D. Sato, S. Asakawa, H. Dong, K. M. Kitani, and C. Asakawa, "Cabot: Designing and evaluating an autonomous navigation robot for blind people," in *Proceedings of the 21st international ACM SIGACCESS conference on computers and accessibility*, 2019, pp. 68–82.

[138] Y. Chen, Z. Xu, Z. Jian, G. Tang, L. Yang, A. Xiao, X. Wang, and B. Liang, "Quadruped guidance robot for the visually impaired: A comfort-based approach," in *2023 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2023, pp. 12 078–12 084.

[139] A. Sardar, M. Joosse, A. Weiss, and V. Evers, "Don't stand so close to me: users' attitudinal and behavioral responses to personal space invasion by robots," in *Proceedings of the seventh annual ACM/IEEE international conference on Human-Robot Interaction*, 2012, pp. 229–230.

[140] D. Chugo, Z. Liu, S. Muramatsu, Y. Sakaida, S. Yokota, and H. Hashimoto, "A dynamic personal space of a pedestrian for a personal mobility vehicle," in *2013 IEEE 4th International Conference on Cognitive Infocommunications (CogInfoCom)*. IEEE, 2013, pp. 223–228.

[141] B. Zhang, M. Kaneko, and H.-o. Lim, "Robust 2d mapping integrating with 3d information for the autonomous mobile robot under dynamic environment," *Electronics*, vol. 8, no. 12, p. 1503, 2019.

[142] Y. Wei, X. Kou, and M. Lee, "Development of a guide-dog robot system for the visually impaired by using fuzzy logic based human-robot interaction approach," in *2013 13th International Conference on Control, Automation and Systems (ICCAS 2013)*. IEEE, 2013, pp. 136–141.

[143] C.-H. Lee, Y.-C. Su, and L.-G. Chen, "An intelligent depth-based obstacle detection system for visually-impaired aid applications," in *2012 13th International Workshop on Image Analysis for Multimedia Interactive Services*. IEEE, 2012, pp. 1–4.

[144] U. R3, "Uno r3," 2024, accessed: Feb. 14, 2025. [Online]. Available: https://docs.arduino.cc/hardware/uno-rev3

[145] H. M. Marhoon, M. I. Mahdi, E. D. Hussein, and A. R. Ibrahim, "Designing and implementing applications of smart home appliances," *Modern Applied Science*, vol. 12, no. 12, pp. 8–17, 2018.

[146] R. Djehaiche, S. Aidel, and N. Benziouche, "Design and implementation of m2m-smart home based on arduino-uno," in *International Conference in Artificial Intelligence in Renewable Energetic Systems*. Springer, 2020, pp. 697–706.

[147] W. Chen, R. Chen, Y. Chen, H. Kuusniemi, and J. Wang, "An effective pedestrian dead reckoning algorithm using a unified heading error model," in *IEEE/ION Position, Location and Navigation Symposium*. IEEE, 2010, pp. 340–347.

[148] U. Steinhoff and B. Schiele, "Dead reckoning from the pocket-an experimental study," in *2010 IEEE international conference on pervasive computing and communications (PerCom)*. IEEE, 2010, pp. 162–170.

[149] W. Elloumi, A. Latoui, R. Canals, A. Chetouani, and S. Treuillet, "Indoor pedestrian localization with a smartphone: A comparison of inertial and vision-based methods," *IEEE Sensors Journal*, vol. 16, no. 13, pp. 5376–5388, 2016.

[150] S.-H. Kong, "Sdht for fast detection of weak gnss signals," *IEEE Journal on Selected Areas in Communications*, vol. 33, no. 11, pp. 2366–2378, 2015.

[151] N. Xiaoji, W. Yan, and K. Jian, "A pedestrian pos for indoor mobile mapping system based on foot-mounted visual–inertial sensors," *Measurement*, vol. 199, p. 111559, 2022.

[152] Y. Li, Y. Zhuang, H. Lan, Q. Zhou, X. Niu, and N. El-Sheimy, "A hybrid wifi/magnetic matching/pdr approach for indoor navigation with smartphone sensors," *IEEE Communications Letters*, vol. 20, no. 1, pp. 169–172, 2015.

[153] A. Valenzuela-Pérez, M. García-Lozano, J. Valenzuela, D. Pérez-Díaz-de Cerio, Á. Hernández-Solana, and A. Valdovinos, "On the use of sniffers for spectrum occupancy measurements of bluetooth low energy primary channels," *Measurement*, vol. 199, p. 111573, 2022.

[154] P. Park, P. Di Marco, M. Jung, F. Santucci, and T. K. Sung, "Multidirectional differential rss technique for indoor vehicle navigation," *IEEE Internet of Things Journal*, vol. 10, no. 1, pp. 241–253, 2022.

[155] I. O. Nyantakyi, Q. Wan, L. Ni, E. O. Mensah, and O. Bamisile, "Acga: Adaptive conjugate gradient algorithm for non-line-of-sight hybrid tdoa-aoa localization," *Measurement*, vol. 224, p. 113820, 2024.

[156] Z. Tian, Y. Zhang, M. Zhou, and Y. Liu, "Pedestrian dead reckoning for marg navigation using a smartphone," *EURASIP Journal on Advances in Signal Processing*, vol. 2014, pp. 1–9, 2014.

[157] V. Gikas and J. Stratakos, "A novel geodetic engineering method for accurate and automated road/railway centerline geometry extraction based on the bearing diagram and fractal behavior," *IEEE transactions on intelligent transportation systems*, vol. 13, no. 1, pp. 115–126, 2011.

[158] M.-S. Pan and H.-W. Lin, "A step counting algorithm for smartphone users: Design and implementation," *IEEE Sensors Journal*, vol. 15, no. 4, pp. 2296–2305, 2014.

[159] W. Kang and Y. Han, "Smartpdr: Smartphone-based pedestrian dead reckoning for indoor localization," *IEEE Sensors journal*, vol. 15, no. 5, pp. 2906–2916, 2014.

[160] G. Klein and D. Murray, "Parallel tracking and mapping for small ar workspaces," in *2007 6th IEEE and ACM international symposium on mixed and augmented reality*. IEEE, 2007, pp. 225–234.

[161] C. Campos, R. Elvira, J. J. G. Rodríguez, J. M. Montiel, and J. D. Tardós, "Orb-slam3: An accurate open-source library for visual, visual–inertial, and multimap slam," *IEEE transactions on robotics*, vol. 37, no. 6, pp. 1874–1890, 2021.

[162] A. I. Mourikis and S. I. Roumeliotis, "A multi-state constraint kalman filter for vision-aided inertial navigation," in *Proceedings 2007 IEEE international conference on robotics and automation*. IEEE, 2007, pp. 3565–3572.

[163] S. Gupta, K. Thakur, and M. Kumar, "2d-human face recognition using sift and surf descriptors of faceâs feature regions," *The Visual Computer*, vol. 37, no. 3, pp. 447–456, 2021.

[164] E. S. Sabry, S. Elagooz, F. E. A. El-Samie, N. A. El-Bahnasawy, and G. M. El-Banby, "Sift and orb performance assessment for object identification in different test cases," *Journal of Optics*, vol. 53, no. 3, pp. 1695–1708, 2024.

[165] H. Weinberg, "Using the adxl202 in pedometer and personal navigation applications. analog devices an-602 appl," Tech. Rep.

[166] G. Welch, G. Bishop *et al.*, "An introduction to the kalman filter," 1995.