UNIVERSIDAD DE DEUSTO

EFFICIENT REMOTE PEDESTRIAN LOCALIZATION TECHNIQUES FOR RESOURCE-CONSTRAINED ENVIRONMENTS

by

Asiimwe Paddy Junior

A dissertation submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy within the Ph.D. Program in Engineering for the Information Society and Sustainable Development

Supervised by

Dr. Luis Enrique Díez
Dr. Odongo Steven Eyobu

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Efficient Remote Pedestrian Localization Techniques for Resource-Constrained Environments

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Abstract

This thesis explores resource-efficient pedestrian localization techniques tailored for outdoor remote resource-constrained environments, specifically focusing on enhancing remote monitoring for elderly people. With a global trend toward aging populations, particularly in underdeveloped regions, and a policy shift from institutional care to community-based aging, it is estimated that by 2050, two-thirds of the world's population over 60 will reside in low- and middle-income resource-constrained countries. This trend is likely to place a higher burden on healthcare, family, and social services since many of these elderly people cannot live independently without assistance from a caregiver.

Remote monitoring systems offer promising solutions to bridge the gap between elderly individuals' needs and available healthcare services, but their adoption is still limited in environments that lack basic infrastructure like stable power and communication networks. Therefore, this study begins by clearly defining ”resource-constrained environments” and systematically reviews existing outdoor remote pedestrian localization systems, evaluating their suitability for these environments. Global Navigation Satellite System (GNSS) technology is highlighted as the most viable option for remote, accurate, long-range, infrastructure-free outdoor localization, but its high power consumption presents challenges when integrated into battery-powered, wearable IoT devices.

This research proposes two methods for efficient GNSS activation specifically tailored to resource-constrained environments to make GNSS feasible. Both approaches aim to minimize unnecessary GNSS activation, optimizing power consumption while ensuring reliable user localization. The first method is a position-based GNSS activation approach

using a Pedestrian Dead-Reckoning (PDR) system. By leveraging a predefined geofence (safe zone) around the user's home, GNSS activation is minimized, turning on only when the user leaves the safe zone. Two implementations of the PDR system were evaluated: acceleration-based and pitch-based. The proposed PDR-based activation method was validated through extensive experimental evaluation, demonstrating significant improvements in power efficiency—up to 90% compared to acceleration-based methods both inside and outside the geofence-without requiring costly infrastructure such as beacons.

The second approach employs machine learning (ML) to drive GNSS activation based on user activity. By leveraging data from inertial sensors, the ML-based system differentiates between everyday "at-home" activities and "walking away" from home. The model activates GNSS only when it detects the specific user activity of "walking away" from home. Four machine learning models were evaluated—Long Short-Term Memory (LSTM), XGBoost, Support Vector Machine (SVM), and Random Forest (RF)—with XGBoost being selected for implementation due to its strong balance between accuracy and computational efficiency. This method proved effective in significantly reducing power consumption, achieving over 40% savings compared to the acceleration-based method.

Experimental validation demonstrated that the proposed PDR-based and ML-driven GNSS activation methods are suitable for deployment in real-world, resource-constrained environments. By selectively activating GNSS, these methods effectively extended battery life, allowing wearable systems to support reliable remote monitoring for longer periods. The proposed solutions successfully addressed the goal of developing resource-efficient localization systems for aging populations, proving to be scalable and cost-effective while enhancing safety for elderly individuals and reducing the burden on caregivers. The targeted power optimizations make these systems feasible for current use and adaptable for future improvements, providing practical, energy-efficient remote monitoring solutions that help elderly individuals age safely in their communities with minimal reliance on resource-intensive infrastructure.

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I wish to express my deepest gratitude to my supervisor, Luis Enrique Díez, whose unwavering trust and support have been instrumental throughout my academic journey. Referring to him as merely my PhD supervisor does not fully capture his profound impact on my development. He has been much more: an esteemed colleague who engaged with me on technical and personal matters, offering guidance on everything from research challenges to family concerns when needed.

His attentive friendship has been a comfort during difficult moments, and I am honored to regard him as a role model. I am deeply thankful for the opportunities he has provided to learn, grow, and carve my path. His invaluable guidance, thoughtful feedback, and mentorship have shaped my professional and personal growth. Thank you for your immense support and for being a true mentor.

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Asiimwe Paddy Junior,

April 2025

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Acronyms

AoA Angle of Arrival

CDMA Code Division Multiple Access

EC Exclusion Criteria

EKF Extended Kalman Filter

GNSS Global Navigation Satellite Systems

GPS Global Positioning System

IC Inclusion Criteria

IMU Inertial Measurement Unit

INS Inertial Navigation Systems

IoT Internet of Things

IP Internet Protocol

LSTM Long Short-Term Memory

ML Machine Learning

MRQ Main Research Question

PCB Printed Circuit Board

PDR Pedestrian Dead-Reckoning

ACRONYMS

PRISMA Preferred Reporting Items for Systematic Reviews and Meta-Analyses

RF Radio Frequency

RQ Research Question

SVM Support Vector Machine

TDoA Time Difference of Arrival

ToA Time of Arrival

TTFF The time to first fix

UWB Ultra-Wideband

WLAN Wireless Local Area Network

XGBoot Extreme Gradient Boosting

CHAPTER

1

Introduction

1.1 Background

Population aging is an unstoppable global phenomenon. Even in countries with relatively young populations, the demographic transition's unavoidable trend toward longer lives and smaller families is taking place. In 2021, 1 in 10 people worldwide were aged 65 or above. The number of people aged 65 years and above will double that of children under five owing to declining fertility, increasing longevity, and the progression of large cohorts into older ages, as illustrated in Figure 1.1. Also, the number of people aged 65 years or older worldwide is projected to more than double, rising from 761 million in 2021 to 1.6 billion in 2050 [1]. The shift in population distribution towards older ages started in highly developed countries in regions such as Europe and North America, but now low and middle-income countries in regions such as Northern Africa, Western Asia, and sub-Saharan Africa are also experiencing the fastest growth in the number of older people. By 2050, two-thirds of the world's population over 60 years will live in low- and middle-income countries [2]. In addition to the challenge of a growing population in these regions, these countries have limited access to some basic resources such as electricity, good shelter, internet, and healthcare, among others [3] i.e., they are resource-constrained

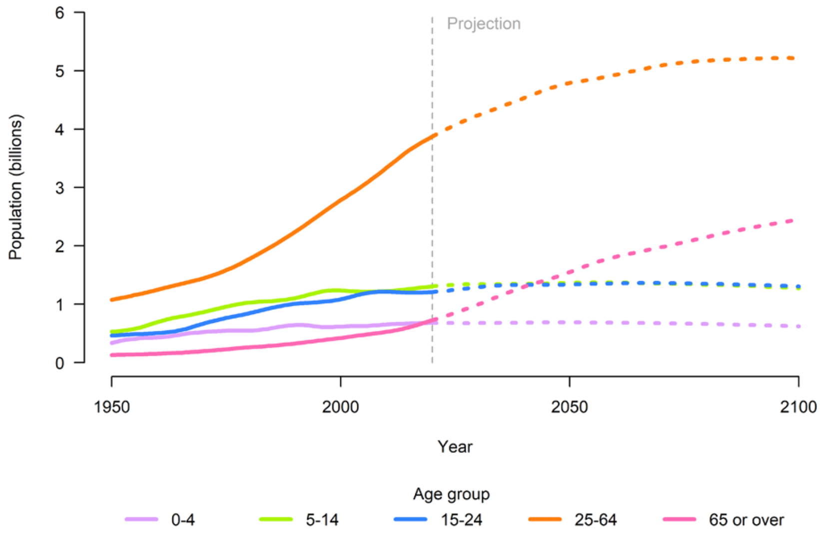


Figure 1.1: Persons aged 65 and above make up the fastest-growing age group[4].

regions. Figure 1.2 shows the projected change in the number of elderly people against the income level for different regions.

To save costs, health care policy should shift from institutionalization to aging in place (in the community). According to the American Association of Retired Persons survey in 2021, if given a choice, 77% of adults over 50 would prefer to age in place, even if they require continuous assistance and health care [6]. Aging in place is defined as remaining in a community-based dwelling during one's late years in life. Many older adults associate "aging in place" with positive attributes, such as maintaining autonomy and independence in a community that offers social connections and access to services. Aging at one's home provides a daily sense of familiarity, such as morning greetings from a household pet, interactions with neighbors, and the ability to surround oneself with physical objects representing cherished memories [7]. Most elderly people choose to age in place for as long as possible because doing so is the most economical option [8].

Old age comes with several non-communicable diseases, such as cardiovascular diseases, kidney failure, arthritis, hypertension, cancer, diabetes, and dementia, among others, which require continuous monitoring and management [9]. For example, research shows that people with dementia have at least a 60% possibility of getting lost in open areas [10]. Research also shows that at least half of adults 65

Figure 1.2: Projected change in the number of persons aged 60 years or over versus gross national income per capita [5].

or older can expect to need care during their older years; caregivers are essential as many of these elderly people cannot live independently without assistance [11].

Family members are the primary source of support and caregiving services for elderly people. These family members give up their job, school, or time to provide this care [12]. For example, in Sub-Saharan Africa, care for the elderly is predominantly a family-centered healthcare system. Families provide most long-term care without organized training or support [13]. This aging population, living in remote regions, has been exposed to the cruelest conditions in resource-constrained environments. Dependence on families alone to provide this care results in unreliable care quality and places economic, psychological, social, and physical burdens on the family caregivers, who tend to be mostly women and girls [14]. Given family caregivers' challenges and complexities, especially in resource-constrained countries, policymakers believe it is no longer feasible to rely on extended families for long-term care of older persons [14]. As such, there is an increase in demand for services in terms of technologies to address the urgent needs of the aging population.

Remote monitoring, based on non-invasive, non-intrusive, unobtrusive wearable sensors, actuators, and communication and information technologies, offers efficient and cost-effective solutions that bridge the gaps between healthcare and where elderly people want to live every day [15]. Such technologies, when implemented correctly, will not only ensure an appropriate quality of life among the elderly persons in their homes but also assist the family and caregivers in providing adequate services to these elderly people in society more easily [16, 17].

These remote monitoring tools can collect many different types of information, but among all of them, the study will focus on location information as this can help us to remotely monitor the elderly person's behavior and infer some basic physical activity information related to the health status (step counter, walking speed, fall detection) [18].

Several remote localization platforms are available on the market, but their adoption rate is extremely low in low-developed countries and rural resource-constrained areas. One primary reason is the scarcity of resources that these systems take for granted. They presume the availability of resources and infrastructures such as cellular networks, Wi-Fi networks, the Internet, digital literacy, and access to the power grid. In other words, these systems are designed for rich countries (highly technologically resourced environments) but are also vitally needed in poor and middle-income countries with resource-constrained environments.

In outdoor environments, location estimation has been successfully implemented using GNSS technology. Today, four major GNSSs are fully operational. Global Positioning System (GPS) from the U.S., GLONASS (Russia), Galileo (E.U), and BeiDou (China) enable worldwide 24/7 positioning. This has made GNSS the de-facto standard for many positioning applications [19]. The use of GNSS technology is mainly in outdoor environments, and this is because GNSS satellites move in Medium Earth Orbit (MEO), and given their low transmission power, GNSS signals often cannot reach indoor environments or dense urban environments [20, 21]. GNSS generally provides a few meters' accuracy in Line-of-sight (LoS) situations. However, its performance degrades in Non-Line-of-Sight (NLoS) scenarios, which often prohibit using GNSS indoors [22].

Although GNSS is the de facto technology for outdoor localization, it is known to consume relatively high amounts of power, which aligns poorly with the stringent constraints of battery-powered devices [23]. This is why many Internet of Things

(IoT) applications, which value battery life more than location accuracy, benefit from options like localization via Low Power Wide Area Networks (LPWANs) such as LoRaWAN [23, 24, 25]. However, this results in large estimation positioning errors [22], which means that, as indicated by the systematic literature review conducted by authors in [26] about state-of-the-art remote pedestrian monitoring systems for resource-constrained environments, GNSS technology is still the best choice for accurate and reliable remote localization of pedestrians. Therefore, research should aim to lessen GNSS' challenges rather than eliminate its use in resource-constrained environments.

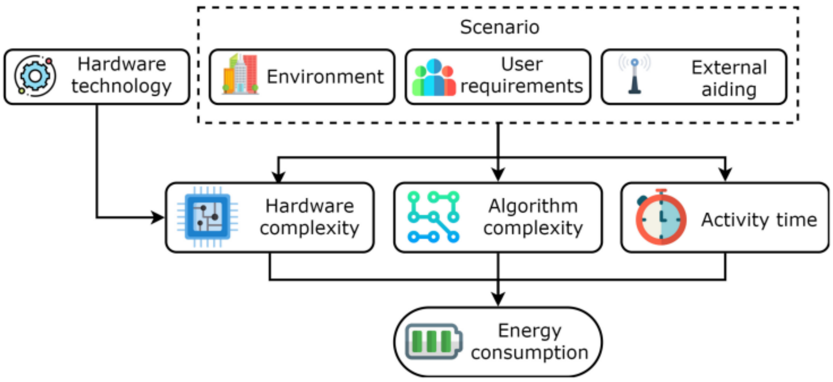


Figure 1.3: Factors influencing a GNSS receiver's energy consumption [27].

Several factors influencing power consumption of the GNSS receivers are illustrated in Figure 1.3. Different GNSS power optimization strategies have been employed to extend the lifetime of IoT devices. Energy-efficient techniques such as assisted GPS (AGPS) [28, 29], extended and autonomous ephemeris prediction [30], cloud computing [31] or snapshot positioning [32, 33, 34] achieve significant power reduction by using external information (external aiding) or delegating part of the GNSS processing. For example, A-GNSS, satellite-based systems are augmented by wireless technologies that transmit assistance data (almanac and ephemeris data) to the GNSS receiver, reducing the Time To First Fix (TTFF) [22]. The requirement of a stable communication channel to access the Internet with sufficient capacity and data rates, which are not available in resource-constrained environments, complicates the applications of these strategies in resource-constrained environments.

Furthermore, GNSS technology has been integrated with other technologies, such as Wi-Fi, Bluetooth Low Energy (BLE), or Inertial Navigation Systems (INS). Although many pedestrian localization systems have tried to reduce power consumption, they still assume that other types of resources are available, such as access to electricity to recharge batteries, communication networks for exchanging data (Wi-Fi, Internet, cellular networks), service providers (coverage), and users with enough economic capacity and digital education to acquire and properly use these devices. In other words, these systems are designed for developed countries and urban centers, yet they are very necessary for less developed countries and rural areas with limited resources.

Also, as the world embraces Internet of Things (IoT) applications, more studies have been conducted on resource-constrained devices, such as IoT devices. It should be noted that the limitations of resource-constrained devices (processing power, memory, energy consumption, etc.) differ from those faced by remote monitoring tools (internet, electricity, cost, etc.) designed for resource-constrained environments as explained more in chapter 2. This underscores the importance and urgency of creating a localization system specifically tailored to the needs and constraints of these resource-constrained environments, and the research presented in this thesis aims to do just that.

1.2 Use Case Description

Motivating Scenario: Jolly's Story

To ground this research in a real-world scenario, consider Jolly a 78 year old mother with dementia living in a remote village in Apac District, Uganda. She has spent much of her life in this rural area, where access to essential services is limited. Her four adult children now reside and work in Kampala, about 400 kilometers away. This distance makes it difficult for them to visit regularly, leaving Jolly largely dependent on a house helper—who, like many in the village, is uneducated and struggles to provide the specialized care that Jolly needs.

Jolly's connection with her children is limited to occasional phone calls, which are not straightforward. The village has no electricity, forcing residents to walk several kilometers to trading centers to charge mobile phones, often just once a *week. To make matters worse, cellular network coverage is unreliable. To place a call, one has to walk to specific elevated spots where the signal is strong enough, sometimes waiting for minutes to establish a connection. Healthcare services are distant and costly, making her regular checkups rare.*

When Jolly manages to reach one of her children, it becomes their responsibility to relay information to siblings about her condition and any urgent needs. This creates a communication bottleneck, as updates are delayed or misinterpreted, making it challenging for her children to coordinate her care effectively. Additionally, their responsibilities are not clearly defined, and without a structured way to track their contributions, ensuring Jolly's well-being becomes an uncoordinated effort filled with uncertainty.

Jolly's situation is not unique. Many elderly people in rural Uganda, like in many other developing countries, face similar challenges, relying on distant family members for support while struggling with limited access to basic resources like electricity, communication, healthcare, housing, and proper care. Financial limitations further hinder the adoption of technology, making it difficult for families to monitor and ensure the safety of their elderly relatives remotely. As a result, existing remote monitoring solutions remain largely inaccessible in such environments despite their potential to address these critical challenges. These realities highlight the urgent need for affordable, low-power, and network-efficient remote monitoring systems that can bridge the gap between aging individuals in rural communities and their families in urban centers.

1.3 Main objective and Specific objectives

The main objective of this thesis is to develop a comprehensive IoT-based remote pedestrian localization system for monitoring elderly people around their homes, especially in resource-constrained environments. The following specific objectives have been defined to achieve the main objective:

- To clearly define the concept of resource-constrained environments and articulate the specific challenges these environments present for remote monitoring solutions. This is intended to show that the limitations of resource-constrained devices, such as IoT devices (processing power, memory, energy consumption, etc.), differ from those faced by remote monitoring tools (Internet, electricity, cost, etc.) designed for resource-constrained environments.

- To conduct an in-depth, state-of-the-art systematic review of the current outdoor remote pedestrian localization systems in order to determine why their adaption rate is extremely low in low-developed countries and rural areas, yet they are very much needed in these resource-constrained environments as well. This objective seeks to evaluate current technologies, identify their shortcomings in resource-constrained contexts, and inform the design of more suitable solutions.
- To propose and experimentally validate a remote pedestrian localization system better adapted to resource-constrained environments. Validating that the system can operate within the limited computational and energy budget of battery-powered devices and evaluate the system in a use-case scenario to show that it meets user needs.

1.4 Scope of the study

This study limits its scope to remote pedestrian location systems designed for outdoor environments, or at least for both outdoor and indoor environments. This is because people in rural areas live mainly outdoors, working in primary industries such as agriculture, forestry, fishing, and hunting [35], including elderly people who spend most of their time outside their homes.

1.5 Methodology

To achieve the above objectives, this research adopts a structured methodological approach comprising the following key steps:

- **Systematic literature review of the state of the art:** Conducting a comprehensive literature review to identify and analyze existing remote pedestrian localization technologies and energy-saving techniques, emphasizing their applicability and limitations in resource-constrained environments.

- **Design and Development of proposed solutions:** Developing resource-efficient methods for GNSS activation:
  - *Position-based GNSS activation using Pedestrian Dead-Reckoning (PDR):* This method leverages a predefined geofence (safe zone) around the user's home, activating GNSS only when the user exits this zone, thus significantly optimizing battery usage.
  - *ML-driven user activity based GNSS activation:* This approach utilizes inertial sensor data to differentiate between ”at-home” and ”walking away” activities, selectively activating GNSS only when the activity of ”walking away” is detected, further enhancing energy efficiency.
- **Experimental Evaluation:** Conducting extensive empirical testing of both GNSS activation methods under real-world conditions to validate their effectiveness, suitability for deployment in resource-constrained environments, and reliability in extending battery life and ensuring accurate localization.

By following this methodology, the project ensured a logical progression from theoretical foundations to a validated solution. Each step fed into the next: the gaps identified in the literature informed the design, the design guided the implementation choices, and the implementation was verified through targeted experiments. This approach provides confidence that the final outcomes are both scientifically sound and practically relevant to the use case.

1.6 Impact

The expected impact of this research is twofold: academic contributions to the field of outdoor remote localization systems and practical benefits for real-world deployments in rural, low-resource environments.

- **Advancement of Knowledge:** This thesis presents a novel approach to energy-efficient localization, demonstrating how inertial sensing and intelligent algorithms can replace or augment traditional GNSS usage in tracking systems. It validates that a significant reduction in power consumption (on the order of 90% less GNSS active time) is achievable without adding expensive infrastructure. This result adds to the body of knowledge in mobile and ubiquitous computing, showing a viable path for machine learning-assisted GNSS duty cycling. Additionally, the comprehensive evaluation of our PDR-based method under realistic conditions provides insights into the trade-offs between localization accuracy and energy savings. Future researchers and system designers can build on these findings to further improve or customize GNSS activation strategies, for example, by adapting them to other contexts such as fitness trackers or wildlife tracking, where similar constraints apply.

- **Enabling Technology in Resource-Constrained Regions:** From a societal perspective, the developed solution can make remote monitoring and tracking more accessible in remote low-resource settings. By significantly extending battery life, the system reduces maintenance and operational costs, as devices require charging or battery replacement far less often. This is crucial for rural healthcare scenarios, such as Jolly's, where caregivers may not have access to charging devices daily. The long-lasting tracking device enables the reliable monitoring of an elderly person or patient for extended periods, thereby enhancing their safety and independence. Moreover, the fact that our approach does not rely on cellular infrastructure or dense networks means it can be deployed in remote villages, disaster sites, or wilderness areas. In such settings, this work could enable new "aging in place" solutions or low-cost tracking services that were previously not feasible due to power constraints.

- **Impact on IoT and Wearable Design:** The principles and algorithms developed here can influence the design of future Internet of Things (IoT) devices for location-based services. Instead of assuming continuous connectivity and power, designers can incorporate smart sensing logic, as presented in this thesis, to make devices more autonomous and efficient. This could promote the development of next-generation wearable trackers that intelligently manage their sensors to strike a balance between performance and battery life. For example, fitness wearables can selectively activate GNSS based on activity patterns, while asset trackers may use low-power sensors combined with infrequent GNSS updates.

- **Policy and Adoption Potential:** Lastly, by addressing the gap between high-tech solutions and the realities of low-resource environments, this research encourages the adoption of remote monitoring in areas where it's most needed. Stakeholders, such as healthcare providers and community organizations in developing regions, may be more inclined to implement tracking programs for the elderly or other vulnerable groups, knowing the technology can function within local resource limitations. In the long term, this can help reduce the healthcare burden through preventive safety measures and improve the quality of life for seniors and their families. The impact of this thesis is therefore reflected not only in technical metrics but also in its potential to empower communities with suitable technology. The findings and prototype from this work demonstrate a practical solution that bridges the gap between cutting-edge research and real-world needs, setting the stage for future deployments and studies in energy-efficient localization.

1.7 Outline of the thesis

The structure of the remainder of this dissertation is outlined below.

In chapter 2, we explain what we mean by a resource-constrained environment and discuss these unique constraints of systems designed for remote pedestrian localization.

In Chapter 3, the study briefly presents an introduction to localization and also presents a systematic review of the state of the art of remote pedestrian localization systems for resource-constrained environments.

Chapter 4 presents the GNSS power optimization strategies and the existing techniques. This chapter also discusses the state-of-the-art of GNSS activation methods. The optimization strategies proposed in this thesis will be related to GNSS activation. That is why the study provides a review of this specific strategy.

Chapter 5 introduces a positioning-based GNSS activation method using the PDR system. In this chapter, the study describes the proposed methodology, provides details about the experiments and results, and provides a summary and conclusion.

Chapter 6 presents a machine-learning method for detecting the activity of walking away from home to another location with the purpose of triggering (activating or deactivating) the GNSS. The approach harnesses the power of machine learning to discern between user motion modes at home and when moving to a different location.

In Chapter 7, the study closes by summarizing the main contributions and drawing the conclusions of this work. The study also outlines possible lines of research for future work.

1.8 Collaborators and Funding

This project has received funding from the European Union's Horizon 2020 Research and Innovation Programme under the Marie Sklodowska-Curie grant agreement No 847624. In addition, several institutions, including the Government of Uganda, backed and co-financed this project through the Makerere University Research Innovation Fund (RIF). This thesis reflects only the author's view, and the Research Executive Agency is not responsible for any use that may be made of the information it contains.

CHAPTER

2

Resource-constrained environments

Whereas many studies have been conducted about resource-constrained devices, more needs to be done about resource-constrained environments. Bormann et al. [36] broadly define resource-constrained devices such as IoT as small devices that, by design, have limited processing and storage capabilities to provide the maximal data output possible with minimal power input while remaining cost-effective. Resource-constrained devices are purposefully designed with processing power, energy consumption memory, and often size limitations. These limitations are not just drawbacks but rather strategic choices that serve specific purposes in the larger context of the Internet of Things landscape [37]. Their benefits include specialized functionality, cost-effectiveness, reduced maintenance, scalability, efficiency and energy conservation, and low network overhead. However, their special attributes also create a unique set of challenges that require innovative solutions, including limited processing power, security, and energy efficiency dilemmas, as these devices often rely on batteries or low-power sources, necessitating careful energy management [37].

On the other hand, Anderson et al. [38] define resource-constrained environments broadly (e.g., low-income communities, low bandwidth environments). These environments provide unique constraints (e.g., cultures where people are unfamiliar with or afraid of technology and environments where power, Internet, and network connectivity are scarce and expensive). Resource-constrained environments provide unique infrastructure and technical and social constraints that demand innovative design approaches. Most less developed countries in Africa, the Middle East, South Asia, Latin America, and the Caribbean have the same challenges of aging populations and the need to monitor their aging population remotely but have to do it in constrained environments.

In this section, the study introduces the seven dimensions that define a resource-constrained environment and shows how current remote pedestrian localization systems do not consider the characteristics of these resource-constrained environments, as discussed below.

2.1 Limited or no access to electricity

According to the World Bank collection of development indicators, Sub-Saharan Africa has the lowest energy access rates globally [39] as illustrated in Figure 2.1. Electricity reaches only about half of its people; roughly 600 million lack electricity. Only 18% of the rural community have access to electricity coverage. For example, in Uganda, the power and energy coverage in urban areas is at 57.2%; however, access drops to 10% in rural areas, and it is only 22.1% nationwide as of December 2022 [40]. Those with electronic devices like mobile phones and smartwatches that use batteries and require periodic charging travel to town centers with electricity coverage to charge them (about four times a month). These town centers are often in a radius of more than 5 km walking distance from their homes. This parameter is key to the design of the localization system, as the devices being used need the power to operate. Even in areas with electricity infrastructure, there is a stagnated supply of electricity (load shedding) due to poor maintenance of power lines, structurally insufficient electricity production on all sources to meet the high power demand, sudden power failures, and downtime, or widespread blackouts. This means that systems designed to depend on a steady supply of electricity will be off for sometimes during these blackouts, thus exposing elderly people who are being monitored.

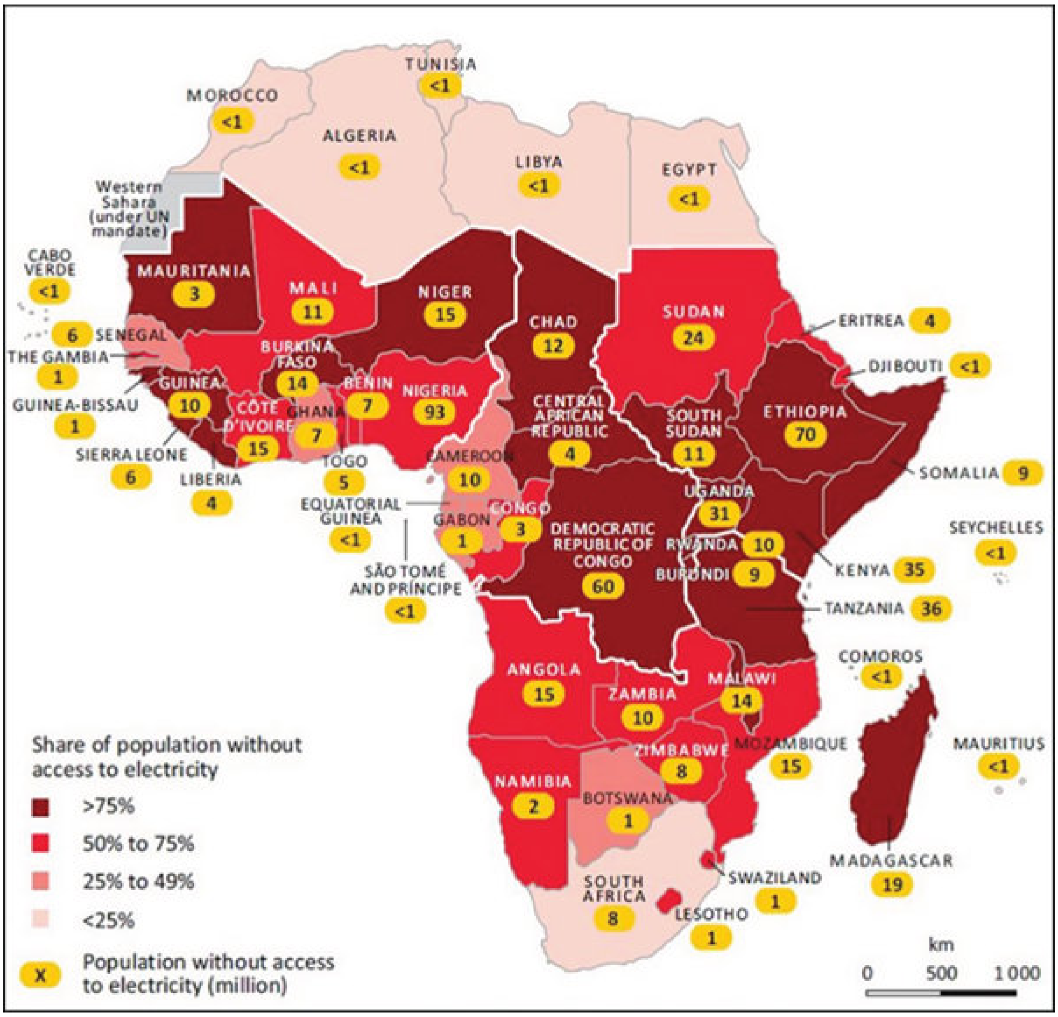


Figure 2.1: Electricity Access in Africa: Map showing access rates and populations without electricity [41].

2.2 Limited or no access to the Internet

According to Africa's Digital Infrastructure Transformation Report 2022 [42], Africa has the lowest number of Internet connections, as fewer than one-third of Africans have access to broadband connectivity, as illustrated in Figure 2.2. Of the 25 least-connected countries worldwide, 21 are located in Africa. Three hundred million Africans live more than 50 kilometers from a fiber or cable broadband connection. At just 36%, Africa's Internet penetration compares poorly with the 63% global average and 92% for Europe. Connection to the stable Internet is a key requirement for most designed remote localization systems and technologies such as assisted GNSS. For example, most energy-efficient GNSS techniques, such as assisted GNSS, snapshot, and extended and autonomous ephemeris prediction, require data exchange with a stable network (Internet) to determine the device position.

2.3 Limited or no access to cellular networks

Mobile phones are the key means most people access the Internet, an essential requirement for most designed remote localization systems. Also, communication technologies such as Global System for Mobile Communication (GSM), Code Division Multiple Access (CDMA), and Long-Term Evolution (LTE), among others, are being used in the designed remote positioning systems on the market as communication networks and mobile phones are the most used devices for localization, especially with commercial systems. The currently designed positioning systems require a stable network to operate, and therefore, it is necessary to analyze mobile (cellular) network connectivity to understand the remaining gap. The GSMA's state of mobile Internet connectivity report 2020 [43] shows that while there has been significant improvement in mobile (cellular) network coverage and affordability of devices, 600 million people still live outside of covered areas, 67% of whom are from Sub-Saharan Africa. Rural people move to raised grounds or town centers where masts have been installed to access the stable network to make or receive calls. Also, these rural areas have no fixed networks (landlines) or fiber optics coverage. With no stable network, the elderly people in these rural areas are denied a chance

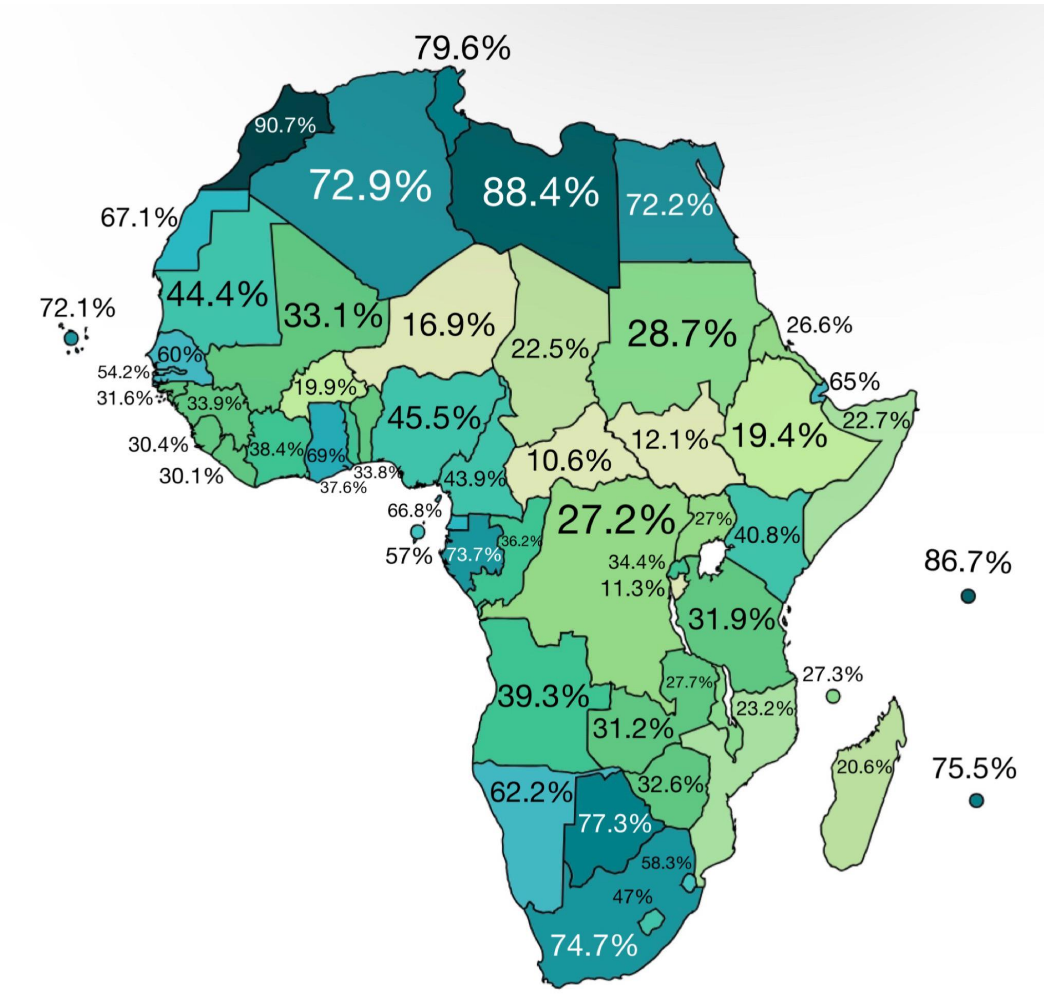


Figure 2.2: Internet access in Africa [41].

to use some of the most used commercial devices, such as mobile phones, and this also makes technologies depending on cellular networks unreliable.

2.4 Lack of digital literacy

The GSMA's state of mobile Internet connectivity report 2021 [44] identifies a lack of literacy and digital skills, such as calling and texting, as well as affordability, as key barriers to mobile Internet adoption. With this report, it is important to note that any system designed to operate in such environments must be able to operate without the user's technical intervention (autonomous). The same report identifies the unconnected people as more likely to be poorer, less educated, older, rural, and women, and thus the need to design a low-cost positioning system that fits their purchasing power.

2.5 Limited access to health care

Rural access to healthcare remains challenging in less developed regions due to urban bias, social determinants of health, and transportation-related barriers. For most patients in these regions, it takes a significant part of the day to reach the nearest hospital facility, which makes it a considerable deterrent to undergo regular screening and checkups. Even when patients eventually reach a hospital, many a time, due to the high patient load and overcrowding, chances are that physicians are already too busy to give any consultation time [45]. For example, in Uganda, one of the best-ranked countries in Sub-Saharan Africa, more than 70% of households are in a radius of more than 5 km to the nearest health facility, whether public or private. The ratio is only one doctor for every 8,300 Ugandans, and 70% of the doctors' population practice in urban areas, where only 20% of the population lives. This worsens the coverage in rural areas: one doctor for every 22,000 people compared to the UK, with 2.8 doctors for every 1000. Because of the distance and poor infrastructure, elders find it quite challenging to walk this distance. Thus, a remote healthcare monitoring solution is needed to bridge the gap between households and healthcare providers and easily monitor them in their homes.

2.6 Rural to urban migration

In addition, the inadequate services and limited access to financial capital in the rural areas have driven educated, semi-educated, and working people in South Asia, Latin America, and Africa, among others, mostly youth, to migrate to urban centers and other countries in search of job opportunities, modern-day technology, productivity, entrepreneurship, modernization, social benefits, and services [46]. These urban centers (towns and cities) are often far from rural communities, making it hard to visit frequently and look after their aging relatives. This has necessitated a solution to monitor these exposed elderly people in rural areas remotely with nobody to look after them seamlessly.

2.7 Poverty

From the Economic Development in Africa Report 2021 [47], poverty levels declined in most African countries: On average, the proportion of African households with a consumption level below the 1.9$ per day poverty line decreased from 40% in 2010 to 34% in 2019. At below 3.2$ per day, the poverty rate fell from 63% to 59%; and at below 5.5 $ per day, it fell from 83% to 80% compared to about 35.28 $ per day for the U.S. This rural population who are primarily in the low-income group and depend upon daily wages, taking a break to visit the hospital is an economic burden. From these statistics, the study can conclude that the majority of the households are not in a position to afford the already existing localization solution because of their limited purchasing power.

2.8 Brief conclusion

The world is embracing Internet of Things (IoT) applications. The main focus is establishing good practices for designing resource-constrained IoT devices (i.e., smart devices) for resource-constrained environments. A set of requirements that include power efficiency, infrastructure, cost, coverage, and autonomy, among others, should be considered while designing systems for these environments, as summarized by Rainer Mautz [48] in Figure 2.3.

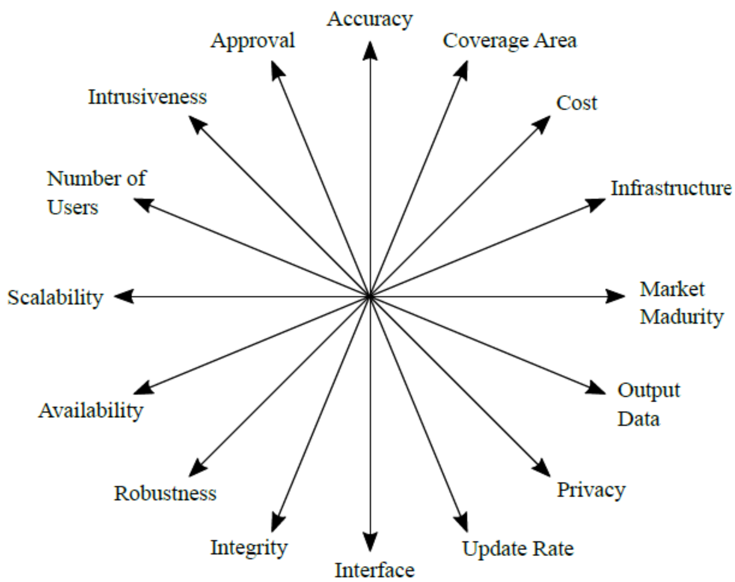


Figure 2.3: General user requirements for a localization system [48].

CHAPTER

3

Remote Pedestrian Localization Systems for Resource-Constrained Environments

Section 3.1 briefly introduces localization and defines several basic concepts. It also presents the main techniques, metrics, methods, and technologies that exist in the state of the art for its resolution. Then, section 3.2 presents a systematic review of remote localization systems designed for resource-constrained environments. This review follows the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) model's guidelines for ensuring the work is reproducible and replicable. The subsection details a comprehensive analysis of the work's main findings and a discussion and recommendations in line with their suitability for a resource-constrained environment.

3.1 Brief introduction to localization

A device's location on Earth has become a crucial requirement in many user applications, including IoT applications. Examples include smart agriculture, ambient assisted living (AAL), wildlife tracking, container tracking, search-and-rescue systems, etc. Current technological advancements enable users to encapsulate these systems in handheld devices, effectively increasing the popularity of localization systems and the number of users. Meanwhile, these mobile devices often have small batteries that must last several years.

Several technical terms with slightly different meanings describe the process of determining a user's location. The following definitions primarily reflect their usage in this work and might be defined slightly differently elsewhere.

- **Localization and Position:**
  Localization and positioning are mainly used to describe the position determination (physical coordinates of sensor nodes) process in wireless sensor networks (WSNs) based on communicating nodes [49]. In English, localization and positioning are often used interchangeably, but slight subtility exists. The use of 'localization' to mean 'positioning' emphasizes that positioning is carried out ad-hoc and cooperatively. The term 'localization' also underlines that the application requires topological correctness of the sensor locations, whereas the absolute coordinate position is not very important. Therefore, localization is mostly associated with rough location estimation for low-accuracy systems such as for locating mobile phones [48]. Positioning is the general term for the determination of the position of an object or a person. It mainly emphasizes that the target object has been moved to a new location. It should be noted that all positioning systems are localization systems, but not necessarily the other way around [50].

- **Navigation:**
  This term includes any method of determining and planning the trajectory of an object. So, you will need to know its position, velocity, and orientation concerning a reference frame. Thus, all navigation systems should include a positioning system, and depending on how the localization information is

computed and provided, localization systems can also be navigation systems. For this reason, both terms are sometimes used as synonyms [50].

- **Tracking:**
  The process of repeated positioning of a moving object or person over time is called tracking. It differs from navigation in that an external agent obtains the position and speed without necessarily requiring the installation of equipment on the object or person being tracked.

- **Geolocation:**
  Geolocation is the process or technique of locating connected electronic devices where the determined location is descriptive or context-based rather than a set of geographic coordinates [48].

Section 3.1.1 presents common measuring principles. Then section 3.1.2 presents localization technologies, i.e., RF-based and inertial-based localization technologies, and section 3.1.3 presents position estimation methods and techniques.

3.1.1 RF measuring principles/metrics

Radio Frequency (RF) localization methods often leverage wireless network infrastructure initially deployed for communication (e.g., LPWANs and Wi-Fi). They translate signal characteristics such as Received Signal Strength (RSS), phase-to-distance, Time of Flight (ToF), or direction estimates and combine these estimates to determine the device's or object's location. The following section describes the signal-measuring principles/features that are most relevant and widely used by localization and positioning methods.

3.1.1.1 Received Signal Strength

The RSS is a measurement of the power present in a received radio signal [51]. Signal strength ranging methods use RF propagation loss models (power attenuation of the signal) to calculate the distance between a transmitter and its receivers. Generally, such models consider the distance between transmitter and receiver, the transmitted power, and the frequency to determine the RSS [52, 53]. The RSS value

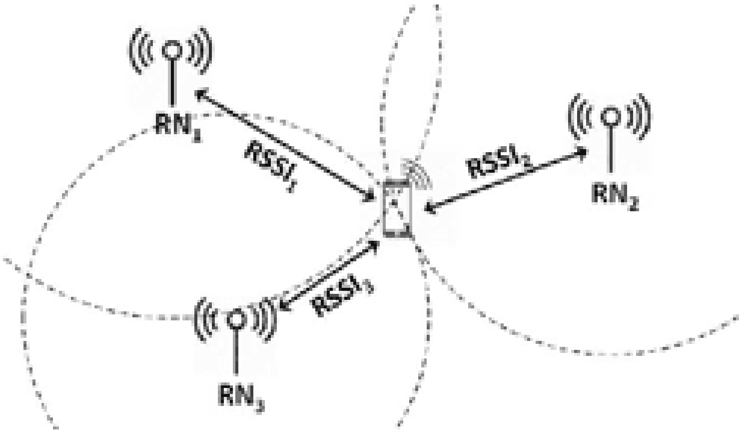


Figure 3.1: Localization based on RSS measurement [54].

is represented in decibel milliwatts (dBm) or milliWatts (mW) and has a typical negative value ranging from nearly 0 dBm (excellent signal) to less than -100 dBm (poor signal) [54]. The location of a transmitter can be calculated with trilateration or multilateration when the distances to at least three receivers are estimated.

Signal attenuation can be exploited for distance estimation based on RSSI values. In free-space situations, electromagnetic waves suffer an attenuation of their power that increases quadratically with the distance to the source and this can be expressed as [50]:

$$P_R = P_T \frac{G_T G_R}{4\pi d^2} \tag{3.1}$$

where P_T is the transmitted power at the emitter, P_R is the RSS or received power, and G_R and G_T are the gains from the receiving and transmitting antennas, respectively, which are separated at a distance of *d*.

A common multilateration technique is to derive an equation system from the receiver locations and the estimated distances from the transmitter to the receiver and solve this system using a least-squares approach [51]. Figure 3.1 shows the user device location relative to the reference points (RN).

The advantage of using RSS is that it can be obtained with no additional hardware using smartphones. Moreover, RSS does not require time synchronization between the transmitter and the receiver. Most crucially, RSS values can be used to implement any localization method, converting them to distance for lateral approaches and storing them in a database for scene analysis. As a result, RSS has emerged as the preferred signal-measuring principle in positioning systems [51].

3.1.1.2 Time of Arrival (ToA) / Time of Flight (ToF)

The ToA is the travel time or time of flight of a radio signal from a transmitter to a receiver. Similar to the RSS-ranging, ToA applies trilateration/multilateration to the estimated distances between a transmitter and at least three receivers [52].

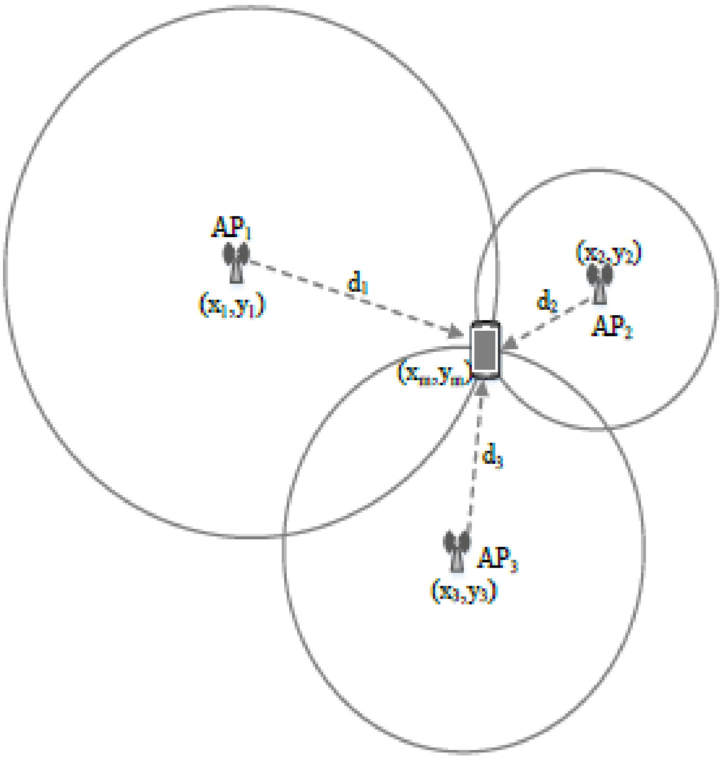


Figure 3.2: Localization based on time of arrival (TOA) measurement [51].

However, ToA relies on the basic principle that the distance between a receiver and a transmitter can be related to their absolute propagation time. Therefore, this method requires very precise synchronization between the transmitter and its receiver clocks, as even one nanosecond error in synchronization translates into a distance error of 30 cm if radio frequency signals are used. This level of synchronization is often impractical for IoT devices and networks, so ToA can be ruled out as a worthwhile localization method for most applications, especially in indoor environments where multi-path conditions are common [48].

Let c be the speed of light, then the distance between *i*th AP and the tag device can be estimated by the following relation [55]

$$d_i = (t_i - t_0) \times c, \tag{3.2}$$

where $t_i$and t_0 are the signal reception and time instant of signal transmission, respectively, and $c = 3 \times 10^8 m/s$. Figure 3.2 illustrates a TOA measurement-based localization system.

3.1.1.3 **Time Difference of Arrival (TDoA)**

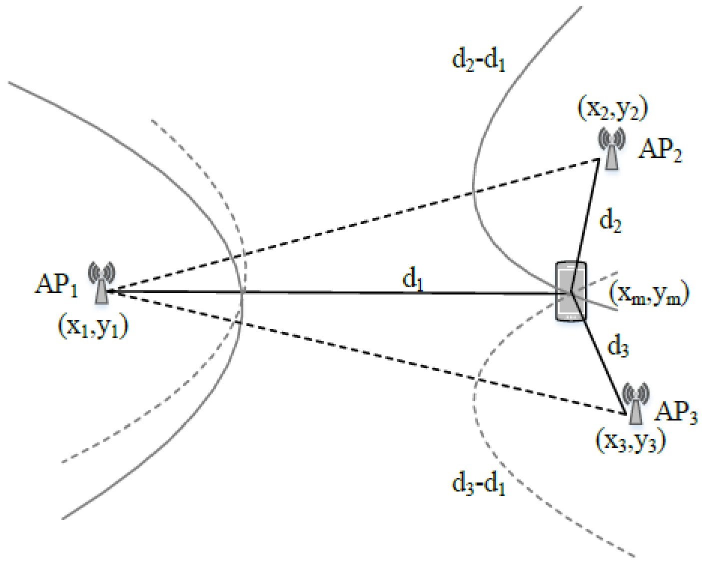


Figure 3.3: Localization based on TDoA measurement [51].

TDoA is the most frequently used distance measurement technique. It is slightly more flexible than TOA, as a transmitting device does not have to be synchronized with the gateways to implement TDoA localization. However, the gateways need to be synchronized. TDOA only requires the time the signal is received and the speed at which it travels, not the time it is transmitted from the receiver [56]. Hence, there is no need to add synchronization hardware that would drain the battery. With a network of precisely synchronized gateways, the location of a transmitter can be calculated based on the TDoA relative to a reference gateway, as shown in Figure 3.3. At least three hyperboles are needed to eliminate location ambiguity, and the transmitter location is estimated at their intersection. This means the time measurements from at least four receiving gateways are required.

$$d_{ij} = (t_i - t_j)c = \sqrt{(x_i - x_m)^2 + (y_i - y_m)^2} - \sqrt{(x_j - x_m)^2 + (y_j - y_m)^2} \quad (3.3)$$

wheret_j and t_i are the time instant of signal reception from AP *j* and *i*, respectively. Geometrically, with a given TDOA measurement, the tag device must lie on a hyperbola with a constant range difference between the two APs.

3.1.1.4 **Round Trip Time (RTT)**

Using RTT, the time the signal takes to travel from a transmitter to a receiver and back is measured. RTT measures the distance without requiring time synchronization between the communicating nodes, allowing its application in uncoordinated mesh networks with the advantage of low complexity and cost [48, 51]. However, range measurements of multiple devices need to be carried out sequentially, which may cause critical latencies for applications where devices move quickly. Wi-Fi RTT was first implemented in Android 9 (API level 28). It is based on a new packet type called a fine timing measurement (FTM) frame, defined by the IEEE 802.11 standard [57]. Subedi et al. [51] explain the FTM protocol as illustrated in Figure 3.4, and RTT is calculated for an FTM message as in [58]

$$RTT = (t_4 - t_1) - (t_3 - t_2) \quad (3.4)$$

The distance (d_{RTT}) between the receiver and transmitter can be estimated by multiplying the speed of light (c) with the RTT as follows

$$d_{RTT} = \frac{RTT}{2} \times c \quad (3.5)$$

Multiple trilaterations are employed with the estimated distance (d_{RTT}) to localize a tag.

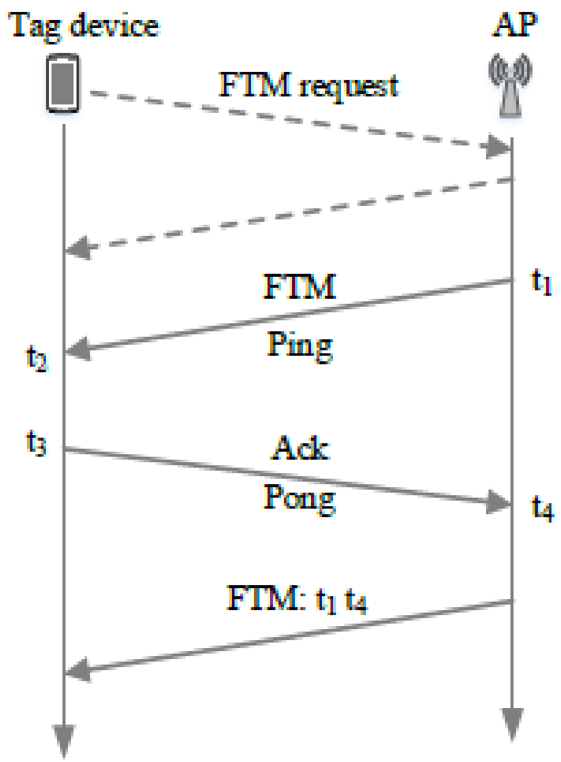


Figure 3.4: The fine timing measurement protocol [51].

3.1.1.5 **Angle of Arrival (AoA)**

AoA metrics for localization have not been incorporated as much as their counterparts. AoA measures the angle at which a signal is received in a reference device. The reference device defines a line that departs from its position with such angle measured, where the target object is assumed to be. The combination of several lines from several reference devices places the target object at the intersection of several lines. At least two reference points and two angles are used (θ_2, θ_1) as illustrated in Figure 3.5. The advantage of this measure is that no time synchronization is required between references. Also, the AoA method is not dependent on signal strength for location estimation. Therefore, channel fading and environment features have minimal effect on location estimation accuracy [23]. The disadvantage is that complex hardware is required to determine AoA, as these systems need arrays of sensors or antennas [20]. Also, a low error in angle computation can lead to a massive error in location estimation. Like TOA, AOA also suffers from line of sight

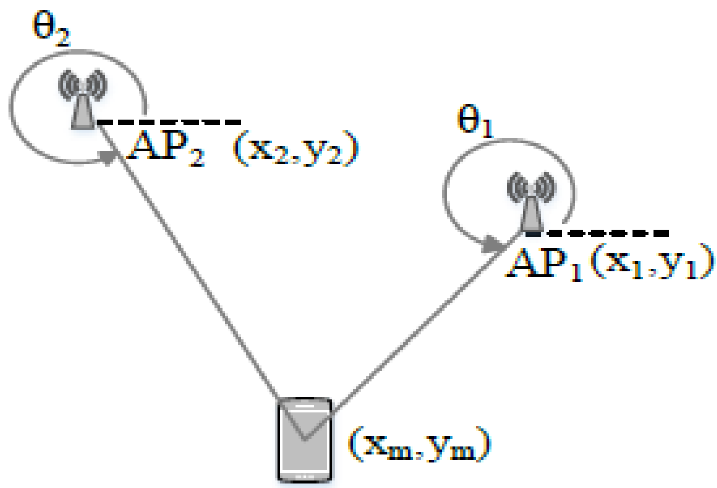


Figure 3.5: Localization based on AoA measurement [51].

(LoS) blockage.

3.1.1.6 **Proximity**

Proximity is defined as nearness in space, time, or relationship. Also called relative positioning/connectivity, the proximity method is one of the cheapest, most straightforward, and basic approaches to wireless localization. As the definition suggests, proximity in the localization system provides symbolic position information if an object is present within an AP's vicinity, and the RSS determines the vicinity [51].

Generally, there are three proximity methods, including sensing physical contact, which uses sensors like touch sensors, pressure sensors, and capacitive field detectors to feel physical contact. The second approach includes observing the wireless signal (RSS) of mobile within the access points range, i.e., after transmission from TX, receivers RX 1 and RX 2 measure their RSS. The receiver's location with the highest RSS is then used as the estimated location of TX, as illustrated in Figure 3.6. This approach relies on only one receiver and can be applied in sparse network deployments [59]. Finally, it observes automatic ID systems, like credit card payment terminals [60]. Generally, localization systems using wireless technologies like BLE [61, 62], RFID [63], and Near Field Communication (NFC) [64] are employed for proximity-based localization system development. However, proximity often leads to higher estimation errors than other localization approaches.

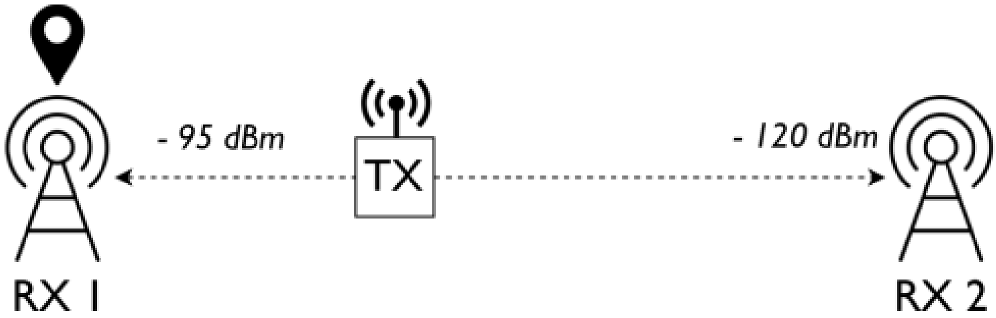


Figure 3.6: The RSS at RX 2 and RX 1 gateway are measured to estimate which gateway is in the closest proximity to TX when TX transmits a signal. The location of that gateway RX 1 is used as the location estimate for TX in this example [59].

3.1.2 Localization technologies

It is important to note the distinction between localization technologies and techniques. In this study, localization technology refers to the set of scientific principles that enable localization/positioning, while a localization technique is a specific method or algorithm to implement these principles. Therefore, the same technology can support multiple localization techniques [20]. When choosing a technology for a resource-constrained environment, one of the first features to consider is the balance between accuracy, power consumption, and coverage. This study categorizes localization technologies into RF or inertial-based.

3.1.2.1 RF-based localization technologies

RF-based systems are the most adopted systems for localization. This is because they offer a good balance of coverage and accuracy compared to other wireless technologies such as infrared or ultrasonic-based localization systems [65]. Examples of RF-based navigation technologies include Wi-Fi [66, 67], Bluetooth [61, 68], ZigBee [69, 70], Ultra-wideband (UWB) [71, 72], GNSS [33, 34], and LPWANs [24, 73].

RF localization methods often leverage wireless network infrastructure initially deployed for communication purposes (e.g., LPWANs, Wi-Fi). They translate signal characteristics such as RSS and ToF and combine these estimates to determine the location of a wireless device or object.

Table 3.1: Summary of the localization technologies and their known performance characteristics. PC: Power Consumption; LA: Localization approach used; VH: Very High; L: Low; M: Moderate; EL: Extremely Low;

Tech	Accuracy	Maximum Range	Maximum Throughput	PC	Technique	LA	Advantages	Disadvantages
GNSS	2m-10m	Global, Outdoors	-	VH	Trilateration	ToA, TDoA	Global, widely available	Only outdoors, high power consumption.
Wi-Fi	m-level	Outdoor:250m, Indoor:50m	600Mbps	M	Fingerprinting, Wi-Fi ranging	RTT, RSS	It is widely available, low-cost.	Good-accuracy localization methods based on fingerprinting require extensive training and relatively low accuracy.
Bluetooth	m-level	up to 100m	24Mbps	L	Proximity, Trilateration, Fingerprinting	AP ID, RSS	Widely available, ultra-low-power protocol stack suitable for the IoT.	Low accuracy. Significant challenges to real-time localization.
UWB	cm-level	up to 300m	460Mbps	M	Trilateration	TDoA, ToA, RSS	High accuracy and precision, moderate costs. It can penetrate various materials, including walls, and is immune to interference from other signals	It is not widely available and needs dedicated infrastructure..
LoRaWAN	TDoA: 20-200m RSS: 1000-2000m	Urban:5km, Rural:20km	37.5kbps	EL	Tri/ Multilateration, Fingerprinting	RSS, TDoA	Ultra-low-power, low-cost, long-range. An asynchronous communication allows the end nodes to be asleep most of the time.	Low accuracy. Low data rates
Sigfox	Range of hundreds of meters	Urban:10km, Rural:50km	100bps	EL	Tri /Multilateration, Fingerprinting	RSS, TDoA	Wide reception range and low energy consumption	It uses unlicensed frequency, but it's a private network. It does not operate in some parts of the world
ZigBee	3m-5m	10m-100m	250kbps	M	Proximity, Trilateration, Fingerprinting	AP ID, RSS	low-power consumption.	It is not readily available on the majority of the user devices, Low data transmission rate.
Inertial	2m	-	-	L	Dead Reckoning	PDR	There is no need for infrastructure in the environment.	Accumulative errors, and it also gives the relative position.

Localization can be done on either a unilateral or multilateral level [59]. In unilateral systems like GNSS, a device calculates its own location based on the measurements it receives from multiple terminals (i.e., satellites or terrestrial network infrastructure). Multilateral systems work the other way around: the location of a transmitting device is located by combining the measurements of multiple receivers. Due to the limited downlink capacity and star topology of LPWANs, it makes more sense to apply the latter.

Table 3.1 summarizes common localization technologies, including their accuracy ranges, coverage, and throughput; it also outlines the advantages and disadvantages of each technology.

The following section discusses different RF-based localization technologies in terms of their technical differences and known performance characteristics.

a) **Satellite (GNSS)** GNSS is a localization technology where the tracker uses satellites to determine its location. Because of its ability to deliver highly free-of-charge, absolutely accurate position, velocity, and time data anywhere in the world, GNSS technology has found its way into an ever-growing range of smart, connected solutions [74]. It provides extremely precise, robust, ubiquitous positioning and timing information independent of telecommunication network infrastructure that connectivity-based technologies lack. There are currently four GNSS constellations in operation: GPS (USA), GLONASS (Russia), BeiDou (China), and Galileo (Europe). Several regional GNSS and augmentation systems complement these.

   While they differ in their implementations, all the GNSS systems are built around the same positioning principle: trilateration. Traditional GNSS-based localization approaches exploit the ToF concept to estimate a receiver's location. When a radio signal leaves a satellite antenna, the current time is included in the message, enabling the receiver to compute the travel time and convert it into a distance measurement or pseudorange (Pr) as illustrated in Figure 3.7, incorporating clock errors. When distance measurements of four satellites are available, the position of the GNSS receiver on Earth can be estimated using tri/multilateration techniques. Depending on the character-

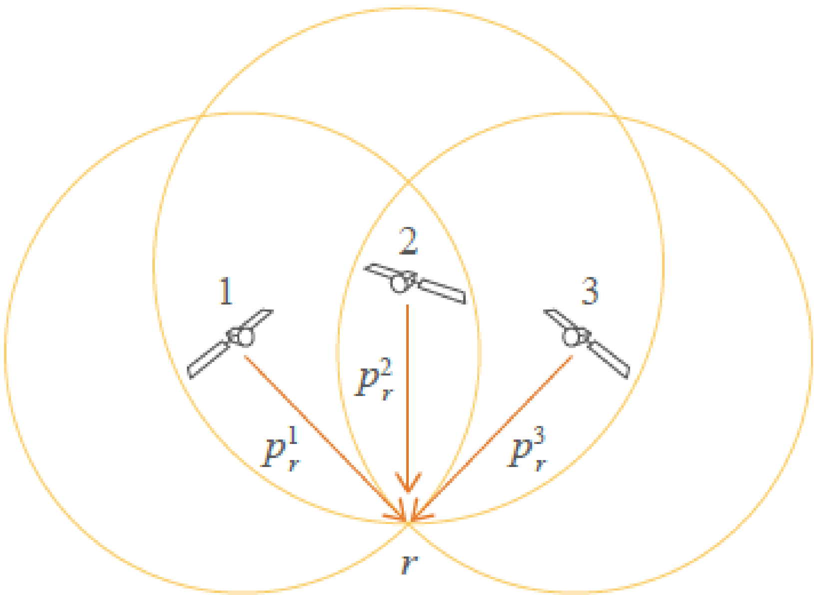


Figure 3.7: Localization through intersecting spheres [75].

istics of the GNSS receiver, environment, and processing method, different accuracies are obtained [59].

Despite these evident advantages, some IoT devices still use inaccurate infrastructure-based approaches due to energy constraints that standard GNSS chipsets struggle to meet. The relatively high energy consumption of the technology aligns poorly with the stringent constraints of battery-powered devices. However, there has been a successful push to significantly reduce GNSS energy consumption in recent years, thanks to rapid advancements in receiver technology and the arrival of several innovative techniques such as snapshot [16], cloud computing [76], extended and autonomous ephemeris prediction, and Assisted GNSS [29] (which dramatically improve the Time to first fix (TTFF) [77]). Most of these techniques require Internet or GSM access and a communication channel such as LTE or NB-IoT with adequate capacity and data rate resources, which are unavailable in resource-constrained environments. Consequently, GNSS is still increasingly attractive for low-power IoT applications, and this paves the way for new applications and more research studies for this technology to fit specific requirements and environments, such as resource-constrained environments.

Single against multiple GNSS constellations
The accuracy performance is a function of the satellites-to-receiver geometry quantified by the Geometric Dilution of Precision (GDOP) factor. A large number of satellites in view results in a better GDOP (improved position accuracy), reduced signal acquisition time, improved position and time accuracy, and higher signal availability, particularly in urban environments where buildings might partially obscure the LoS to the satellite. Single constellation receivers are the most commonly used, as multi-constellation receivers are more costly and consume more power. GPS is the most used single constellation receiver [21].

Single vs dual frequencies
Processing GNSS signals in multiple (dual) frequencies provides significant positioning accuracy and better protection against local disturbances such as interferences or multipath. Also, using multi-frequency receivers is the most effective technique to eliminate the ionospheric error from the position calculation [78]. However, this high performance comes at the cost of an increase in overall energy consumption and high cost compared to single-frequency receivers [21].

b) **WLAN (Wi-Fi)**
WLAN, also called "Wi-Fi," transmits and receives data using electromagnetic waves, providing wireless connectivity within a coverage area. These waves replace traditional LAN data transmission methods like twisted pairs, coaxial, and optical fibers. Wi-Fi can be used to estimate the location of a mobile device within that network and is the most well-known approach for indoor positioning systems (IPS). Wi-Fi signals are a tempting approach since Wi-Fi access points are readily available in many indoor environments in developed countries, and it is possible to use standard mobile hardware devices [48]. Three approaches are commonly used to locate a user using WLAN technology. The first approach uses the relative strength of several known Wi-Fi bases to solve the position using a multilateration method. The

second approach is to use the propagation model of a known antenna, calculating the distance to a known base. The third approach is fingerprinting, as explained in the following section 3.1.3.3. Like other RF infrastructures, the Wi-Fi infrastructure supports fingerprinting-based systems, which have been a research trend because it is much more accurate than other techniques.

c) **WPAN**

A wireless personal area network (WPAN) is a type of personal network that uses wireless communication technologies to communicate and transfer data between the user's connected devices. Unlike a WLAN, a connection made through a WPAN involves little or no infrastructure or direct connectivity to the world outside the link. This allows small, power-efficient, inexpensive solutions to be implemented for various devices.

WPANs such as BLE and UWB offer high penetrating power, low-power consumption and transmission, good positioning accuracy, and little or no interference and multipath effects for indoor environments compared to other IPS and technologies like Wi-Fi. Still, they are unsuitable for outdoor environments because of their limited range (10m-300m) and are expensive to scale.

i) **ZigBee technologies**

ZigBee is a wireless technology standard regarded as a low-rate WPAN. It is mainly designed for applications that demand low data usage, long battery life, and high security but do not require extensive data throughput [79]. The IEEE 802.15.4 standard is used to build the ZigBee protocol stack. ZigBee-based wireless devices use the 868 MHz, 915 MHz, and 2.4 GHz frequency bands, and also 250 kbp is the highest data rate [80]. The signal range coverage of a ZigBee node is up to 100m in free space, but in indoor environments, typically 20m to 30 m [59].

RSSI measurements are commonly used to determine the range between two ZigBee-enabled devices. ZigBee is vulnerable to interference from a wide range of operational signal types running at the same spectrum because it runs without a license inside ISM bands [81]

The advantage of RSS localization is that it is nearly implemented in all ZigBee receivers, so it does not require dedicated hardware. Despite its low accuracy, as it can suffer from multipath interferences and noise, it still had a fair accuracy of 10m for a 100m range because it was deployed outdoors with no strong multipath interference.

ii) **Ultra-Wide Band**

Ultra-wideband (UWB, Ultra-wideband, or Ultraband) is a wireless communications technology for high-bandwidth, short-range communication holding the properties of strong multipath resistance and, to some extent, penetrability for building material, which can be favorable for indoor distance estimation, localization, and tracking [82]. UWB has a frequency of over 500 MHz and a carrier frequency of over 2.5 GHz. It is also free of interference because its spectrum is quite distinct. As a result of all of these characteristics, UWB technology is a suitable option for indoor positioning [83]. However, it is expensive to scale because of the need to deploy more UWB sensors in a wide coverage area to improve performance.

Compared to time-based techniques, the RSSI-based technique does not fully utilize the wide bandwidth of UWB to improve localization accuracy. TOA, TDOA, and AOA leverage the high time resolution of UWB short-duration signals to increase localization accuracy compared to other methods [84].

iii) **Bluetooth**

Bluetooth is a short-range WPAN technology with a wavelength of roughly 12.5 cm that operates between the frequencies of 2.4 and 2.48 GHz. In contrast to ZigBee, the Bluetooth standard is a proprietary format managed by the Bluetooth Special Interest Group. The new Bluetooth version, termed BLE, can cover a range of 70–100m and provides 24Mbps with higher power efficiency. Beginning with this version, AOA may now measure the direction angle of a received or transmitted signal. Like other RF technologies, Bluetooth location calculation might also be based on time or RSSI. Bluetooth is compatible with various devices, including laptops, desktops, smartphones, and PDAs. Bluetooth offers high security, low cost, small size, easy integration into portable devices, and power efficiency, allowing transmitters to function for months or even years on a single charge [48, 85, 86]. On the other hand, Bluetooth-based localization systems can only provide a precision of 1 to 3 meters and have a 20-second latency [87], which is unsuitable for real-time monitoring. Also, when using Bluetooth, it's essential to consider signal attenuation, multipath effects, and fluctuating signal strength [88].

d) **LPWAN technologies**

LPWAN, which emerged in 2013, stands for low-power wide-area network. LPWAN describes a group of network technologies designed to wirelessly communicate small data packets at low transmission data rates over relatively long distances using lower power than standard network technologies like Bluetooth or WLANs. Small data packet transmission, low power consumption, and comprehensive signal coverage are ideal for IoT and M2M devices and applications [89].

Like other RF-based methods, LPWAN localization methods often leverage wireless network infrastructure initially deployed for communication, as LPWAN signals can simultaneously be used for communication and localization. This means no additional hardware cost or energy is consumed for localization purposes, a significant benefit for many energy-constrained applications or resource-constrained environments.

In recent years, two major types of LPWAN technologies have emerged: networks based on non-cellular technology and cellular networks. These technologies can operate on licensed or unlicensed frequencies, with proprietary or open standards.

i) Non-cellular-based technologies: Sigfox and LoRaWAN

Sigfox and Long Range Radio WAN (LoRaWAN) are the most important unlicensed cellular technologies. **Sigfox** is one of the most widely used low-power wireless networks today. This proprietary ultra-narrow band

LPWAN technology runs over a network in the frequency bands 868 MHz in Europe, 915 MHz in North America, and 433 MHz in Asia, which are unlicensed Industrial, Scientific, and Medical (ISM) [89, 90]. Sigfox network can transmit messages over 30 to 50 kilometers in rural areas, 3 to 10 kilometers in urban settings, and up to 1,000 kilometers in line-of-site applications. The number of devices per access point is as high as one million. Its packet size is limited to 150 messages of 12 bytes per day. Even though Sigfox provides bidirectional communication, its downlink capacity is constrained. Down-link packets are limited to four messages of 8 bytes per day [89, 90].

LoRa is a physical layer technology that operates in unlicensed ISM frequency bands. It´s based on the chirped spread spectrum (CSS) technique, which ensures full bidirectional communication, and the generated signal has low noise levels, enables high interference resilience, and is difficult to detect or jam [90]. LoRa is a single-hop technology that relays the messages from LoRa sensor nodes to a central server via gateways [91].

To support LoRa on the Internet, The LoRa Alliance has created LoRaWAN, which provides network and upper-layer functionalities. LoRaWAN is an LPWAN protocol and system architecture developed by the LoRa Alliance [92]. LoRa Alliance is an open, non-profit association with many global members from telecommunication companies [93]. A key characteristic of the LoRa-based solutions is ultra-low power and long-range requirements, which allow for the creation of battery-operated devices that can last up to 10 years, a key requirement for remote pedestrian localization systems designed for resource-constrained environments. LoRaWAN supports three classes of end devices, i.e., Class A, Class B, and Class C [94], to meet the diverse needs of a wide range of IoT applications [22].

Contrary to cellular networks, where end devices set up a point-to-point connection with a single gateway, LoRaWAN implements a star topology, enabling multiple gateways to simultaneously receive transmissions from a device and relay them to a network server through UDP/IP protocol [23].

LoRaWAN has six spreading factors (SF7–SF12) to adapt the data rate and range tradeoff. LoRaWAN has six spreading factors (SF7–SF12) to adapt the data rate and range tradeoff. The higher spreading factor results in a more extended transmission range and the lowest data rate [95]. Depending on the channel bandwidth and the spreading factor, LoRa supports data transmission rates ranging from 300bps to 50kbps.

The most commonly used frequency bands of LoRaWAN are 868 MHz in Europe, 915 MHz in North America, and 433 MHz in Asia. The adaptive data rate provided by LoRa technology enables optimization of power consumption for different IoT applications. LoRaWAN can provide between 2 to 5 km coverage in urban areas and around 15 km or more in rural areas (line of sight). The maximum data rate of around 100 kbps in both uplink and downlink directions is possible with LoRaWAN in North American deployment [92].

ii) Cellular-based technologies: LTE-M and NB-IoT

NB-IoT, which stands for Narrow-band Internet of Things, and LTE-M, which stands for Long Term Evolution for Machines, are wireless telecommunications technology standards developed by the 3rd Generation Partnership Project (3GPP), the international standards group in charge of all major mobile telecommunications standards, including the GSM standards and Long Term Evolution (LTE) standards. Unlike LoRaWAN and Sigfox, LTE-M and NB-IoT are operated by wireless network providers, i.e., they operate in licensed frequency bands [59, 89].

Compatible with current LTE networks, **LTE-M** provides extended coverage comparable to LTE networks, coverage for M2M applications similar to that of 5G networks, and offers a seamless path to 5G M2M solutions. LTE-M provides variable data rates and support for real-time and non-real-time applications. It supports low-latency and deferred traffic applications that can operate with latencies as short as a few seconds. It has low power requirements and supports operations ranging from low bandwidth to as high as 1Mbps in uplink and up to 384 kbps in downlink [23]. LTE-M also supports devices with an extensive range of message sizes. LTE-M typically consumes more power than other LPWANs like Sigfox, decreasing the battery lifetime [96].

NB-IoT can coexist with LTE and GSM in the licensed frequency bands of 700MHz, 800MHz, and 900MHz. NB-IoT is designed to optimize and reduce the functionalities of LTE so that it can be used for infrequent data transmissions with low power requirements. NB-IoT supports up to 200 kbps for downlink and 20 kbps for uplink data rates [23]. The maximum payload size for each message is 1600 Bytes [89].

3.1.2.2 **Inertial-based localization technologies**

Whereas wireless positioning relies on external signals transmitted from fixed reference points, such as GNSS satellites, Wi-Fi access points, or Bluetooth beacons, to determine the user location, dead reckoning, also known as inertial navigation, estimates a device's present position based on its previous calculated position and subsequent movement data. Relies on internal sensors such as accelerometers, gyroscopes, and magnetometers to estimate direction and distance traveled [97].

This section outlines Pedestrian Dead Reckoning (PDR) approaches based on Inertial Navigation Systems (INS), which consist of a processing unit and an Inertial Measurement Unit (IMU) as the main components.

Inertial Navigation Systems

An inertial navigation system is an electronic system that uses various environmental sensors to detect and measure an object's change in motion. Using sensor data, an INS can estimate the position of an object or the vehicle relative to its starting point, a process known as dead-reckoning (DR), referenced as PDR in the case of pedestrian navigation.

If the initial position and orientation are known, the moving object's subsequent positions, orientations, and velocities (direction and speed of movement) can be updated continuously via DR without needing external reference positions. This independent operability (at least temporarily without external infrastructure) is the main argument for using INS for pedestrian navigation, more so in resource-constrained environments. Also, nearly all smart devices, especially smartphones, are incorporated with inertial sensors that help detect the user's location relative to a particular start location, and this has allowed INS to play an integral role in our movements. Modern INS is accurate, reliable, and affordable for many emerging applications and markets.

Inertial Sensors

Several types of sensors are used in inertial navigation systems; however, the two primary types are accelerometers and gyroscopes.

- **Accelerometers**
  Accelerometers are motion sensors that measure an object's linear acceleration (rate of change in velocity) relative to a local inertial reference frame. As most objects can move in three-dimensional space, it is typical to use three accelerometers mounted orthogonally, each with an axis 90 degrees to the others.

- **Gyroscopes**
  Angular rate sensors, commonly known as gyroscopes, measure rotational velocity (angular rate), and again, as most objects are free to rotate in three-dimensional space, using three gyroscope axes is typical. They are also mounted on the object orthogonally and aligned as best as possible with the three accelerometer axes. They are usually given the X-axis, Y-axis, and Z-axis, as illustrated in the figure 3.8.

A typical INS will have other in-built sensors or connected equipment to provide a more comprehensive dataset (for absolute positioning) that is broader than motion alone, such as:

- **Magnetometers**
  A magnetometer detects and measures the strength and direction of the Earth's magnetic fields to determine heading. Magnetic heading derives a north-related direction using a combination of the Earth's magnetic field strength. Three magnetometers measure the strength of the magnetic field [98] to provide a three-dimensional orientation with respect to magnetic north.

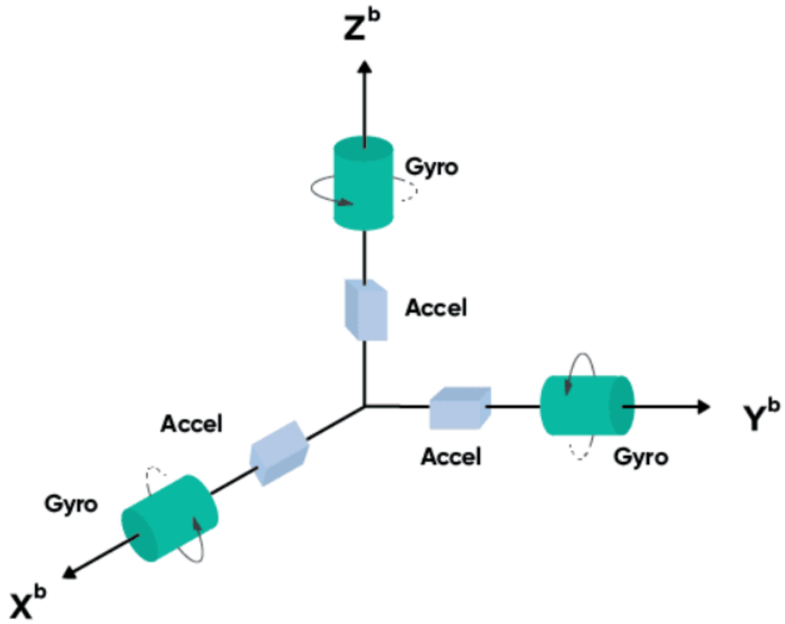


Figure 3.8: Gyroscopes and accelerometers in the three axes of movement. Each gyroscope and accelerometer is positioned at 90 degrees to the others (orthogonally) [48].

- **Pressure sensors**
  Pressure sensors measure external pressure. For example, an air pressure sensor (barometer) can be used to determine altitude, and a water pressure sensor can be used to determine depth in underwater applications.

Inertial Measurement Unit

The most common technology used in the production of inertial sensors today is Micro-electromechanical systems (MEMS), including three gyroscopes (angular rate sensors), pressure, three orthogonally arranged accelerometers (motion sensors), and magnetometers (three perpendicular sensors for measuring the strength and direction of a magnetic field), are the most utilized among the inertial sensors [97].

The inertial measurement unit performs inertial sensing on a modern INS. It's also known as a motion reference unit (MRU) or an inertial reference unit (IRU). The IMU outputs raw motion data used by other parts of the INS, typically in conjunction with other sensors. In addition, IMUs may include additional sensors, such as magnetometers and barometers [50].

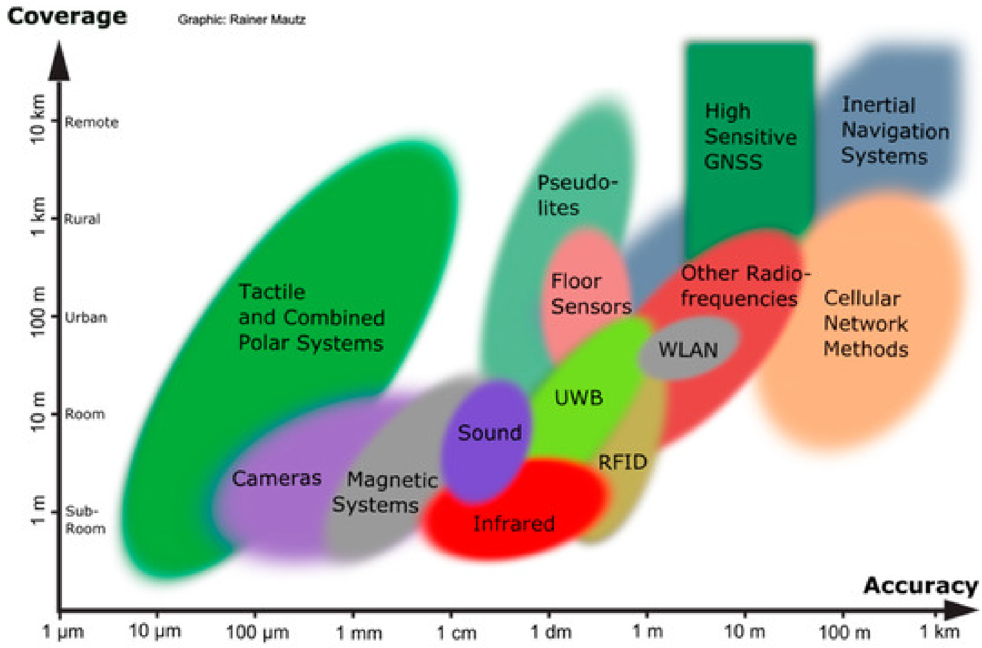


Figure 3.9: Comparison of accuracy and coverage offered by different localization technologies [48].

Integrated inertial sensors only estimate relative position, with accuracy deteriorating over time. Inertial data is most useful when combined with another technology capable of absolute rather than relative positioning, and this is because the inaccuracy of the process is cumulative. To determine the precise location and improve accuracy, they should be used in combination with other technologies (hybridization), such as GNSS [99, 100], UWB [101], Wi-Fi [102], LPWAN [103] and Bluetooth [104, 105].

3.1.2.3 **Hybrid Localization Systems**

Many other technologies not considered in this work can be used to implement localization systems based on position fixing, including cameras, infrared, cellular networks, FM radio signals, visible light, RFID, and magnetic fields. Figure 3.9 compares the most common technologies in terms of accuracy and coverage.

The systems that rely on technology fusion are called "hybrid." While in studies like [106], the term "hybrid" refers to the combination of different techniques like AoA, TDoA, and so forth, in the context of this work, “hybrid” refers to the combination of various technologies, such as GNSS and Wi-Fi technologies.

The hybrid method takes advantage of the strengths of one system and combines it with another system with strengths where the first system exhibits inhibitions to compensate for the limitations of single model positioning technologies [86]. In these systems, one of the technologies is commonly considered more relevant for estimating the user’s location, and the rest are complementary. They are used to improve the system metrics, such as energy consumption, robustness, reliability, cost, accuracy, and coverage area [107]. The following evaluation metrics explain the parameters that can affect the efficiency and performance of a localization system.

Energy consumption

Energy efficiency is of primary importance from a localization perspective for systems designed to operate in resource-constrained environments and IoT systems. These systems are embedded in different environments for an essential purpose. Therefore, long battery life and low energy consumption are fundamental points for these systems. Possible factors that can influence the energy consumption of any localization system includes periodicity (frequency of transmitting a reference signal), transmission power, and computational complexity of the localization algorithm.

Coverage

The reception range of the technology used for localization is also of primary importance in evaluating any system. Coverage describes the spatial extension where a positioning system must guarantee system performance. The choice of the reception range depends on the application and the environment in which the localization system is to be used. For example, GNSS technology is mostly preferred for outdoor localization because of global coverage [108].

Accuracy

One of the most important features of the localization system is the accuracy with which the user position is obtained. Accuracy is the closeness of agreement between a measured quantity value and a true quantity value of a measured [48]. The presence of obstacles and multipath effects provide a challenging space for the localization systems. Therefore, the system must limit the impact of multipath effects and other environmental noises to obtain a highly accurate system. The pedestrian localization system should ideally locate the user with 5 m accuracy.

Cost

Cost is one of the most crucial and significant variables to consider while developing and implementing a localization system. The localization system's overall cost comprises the cost of the necessary hardware and software equipment, the cost of services and their performance, and the cost of the deployment environment. After completion of the design process, additional factors like power consumption, maintenance, and expanding the system to provide more services directly impact and increase the cost of the localization system [97]. An ideal localization system should not incur any additional infrastructure costs as well as don't require any high-end user device or system that is not widely used, and more so for the environments considered in this study.

Reliability

Reliability is the likelihood of getting error-free feedback from systems at a specific time and location. In an emergency, location-based systems might report erroneous locations, making the situation much more out of control, particularly in unforeseen circumstances where reliability cannot be guaranteed [109]. Therefore, the localization system ought to consider the technology's reliability as much as possible in terms of the lack of material ages, environment changes, and complexity of the localization technology.

3.1.3 Position estimation methods and techniques

Many localization methods exist, and generally, their performance depends on error sources such as end-device-related errors like motion diversity, environment-related errors, for example, Non-Line of Sight (NLoS), gateway-related errors like network geometry and time synchronization, and data-related errors that are mainly associated with fingerprinting localization [110]. In the following, we discuss all the common positioning methods.

3.1.3.1 **Lateration / Trilateration / Multilateration**

All three terms refer to determining the position of an unknown object (tag device) based on measuring the distance from more than two known reference nodes (access points) with their known actual location coordinates. Given the distance to an access point (AP), it is known that the tag device is situated along the circumference of a circle centered at the AP. This circle has a radius equivalent to the distance between the tag device and the AP. At least three noncollinear APs are needed for 2D localization, whereas at least four noncoplanar APs are required for 3D localization to perform a trilateration operation [51]. As the number of APs (anchor nodes) increases, the system's accuracy and reliability will also increase. Lateration-based positioning can be applied to a set of distances no matter what distance estimation method (ToA, TDoA, RTT, AoA, and RSSI) is used. In some studies, multilateration is mainly used to indicate that the distances originate from TDoA.

Given B APs with location coordinates $x_i = (x_i, y_i)$ $(i = 1, 2, \ldots, B)$ and an unknown tag device location $x = (x, y)$. The distance between the tag device and the APs is d_i $(i = 1, 2, \ldots, B)$. The 2D relationship between the APs' positions and the distances to the tag device can be expressed as [111]:

$$\begin{bmatrix} (x_1 - x)^2 + (y_1 - y)^2 \\ (x_2 - x)^2 + (y_2 - y)^2 \\ \vdots \\ (x_B - x)^2 + (y_B - y)^2 \end{bmatrix} = \begin{bmatrix} d_1^2 \\ d_2^2 \\ \vdots \\ d_B^2 \end{bmatrix} \tag{3.6}$$

Equation 3.6 can be represented as Ax = b, where b and A are defined as follows:

$$A = \begin{bmatrix} 2(x_B - x_1) & 2(y_B - y_1) \\ 2(x_B - x_2) & 2(y_B - y_2) \\ \vdots & \vdots \\ 2(x_B - x_{B-1}) & 2(y_B - y_{B-1}) \end{bmatrix} \tag{3.7}$$

$$b = \begin{bmatrix} d_1^2 - d_B^2 - x_1^2 - y_1^2 + x_B^2 + y_B^2 \\ d_2^2 - d_B^2 - x_2^2 - y_2^2 + x_B^2 + y_B^2 \\ \vdots \\ d_{B-1}^2 - d_B^2 - x_{B-1}^2 - y_{B-1}^2 + x_B^2 + y_B^2 \end{bmatrix} \tag{3.8}$$

The tag device's location can be estimated using the least squares method as follows [112]:

$$\mathbf{x} = (\mathbf{A}^T\mathbf{A})^{-1}\mathbf{A}^T\mathbf{b}$$

3.1.3.2 Angulation/Triangulation

In contrast to trilateration, triangulation uses angle and distance measurements to estimate the position of the tag device. The angulation method relies on the geometric measurement of the arrival angle of the signal. The received signal angles relative to multiple APs are obtained using AoA techniques, as already discussed in section 3.1.1.5. To estimate the location of an object in 2-D and 3-D space, it is enough to know the position of two and three reference nodes, respectively. The accuracy of this method improved by the number of reference nodes.

Given the known location coordinates of the APs and after calculating the AOA, as shown in Figure 3.5, the location of the tag device can be calculated as follows [113].

$$x_m = \frac{y_2 - y_1 + x_1 \tan\theta_1 - x_2 \tan\theta_2}{\tan\theta_1 - \tan\theta_2} \tag{3.9}$$

$$y_m = y_2 - \frac{(x_2 - x_1)\tan\theta_1 - (y_2 - y_1)}{\tan\theta_1 - \tan\theta_2}\tan\theta_2 \tag{3.10}$$

where θ_2 and θ_1 are the estimated angles of incidence at two APs with their location coordinates (y_1, x_1) and (y_2, x_2), respectively.

This method is accurate and sensitive to LoS between anchors and beacons. Bluetooth 5.1 uses a similar approach for positioning systems [114].

3.1.3.3 Fingerprinting

Fingerprinting, also known as scene analysis, is a pattern-matching localization method that estimates a wireless device's location without knowing the receivers' location. The fingerprinting method is based on RSS radio frequencies, although there are other approaches, such as sounds and visual images, as well [115]. This method consists of an online step and an offline step. In the offline step, also called the training stage, someone collects training data in the area where they want to locate their devices (mapped based on the received RSSI signals). Messages must be transmitted from known locations all over the area of interest to build a representative training database.

In the online step, also called the serving stage, RSS measurements of newly received transmissions are matched to the fingerprints in the training dataset to estimate a transmitter's location, e.g., by applying a k-Nearest-Neighbors (kNN) analysis [52], maximum likelihood estimator (MLE) [116], decision trees, etc. Numerous algorithms match online and offline values on a map, and these can be divided into probabilistic and deterministic methods. Probabilistic methods are based on the probability of the existence of RSS samples. It provides high performance with more computation requirements, increasing the cost and time. Deterministic techniques such as KNN are simple and have acceptable performance [51].

Fingerprinting has better positioning accuracy and performance when compared with ranging methods, especially if used in small ranges. However, these fingerprint-based methods require a comprehensive survey of the environment to build a database and update the database regularly to reflect changes in dynamic environments and complex signal fading of different environment situations (e.g., weather changes). It is even more unsuitable when the object being tracked moves in areas much larger than the considered area during the offline phase, and this is very likely with the objects and the environments being considered in this study.

3.1.3.4 **Dead Reckoning (DR) localization method**

Dead reckoning is the process of estimating a position based on previously calculated positions and known or estimated speeds, heading, and course over the elapsed time. An inertial navigation system is the main type of sensor used. One fundamental characteristic of the DR method is that it is self-contained, i.e., it does not require the existence of landmarks or reference points in the environment. Knowing the starting position, the heading, and the speed during the integration period is what is necessary [50]. A disadvantage of dead reckoning is that the inaccuracy of the process is cumulative, so the deviation in the position fix grows with time, as depicted in Figure 3.10. The reason is that new positions are calculated solely from previous positions.

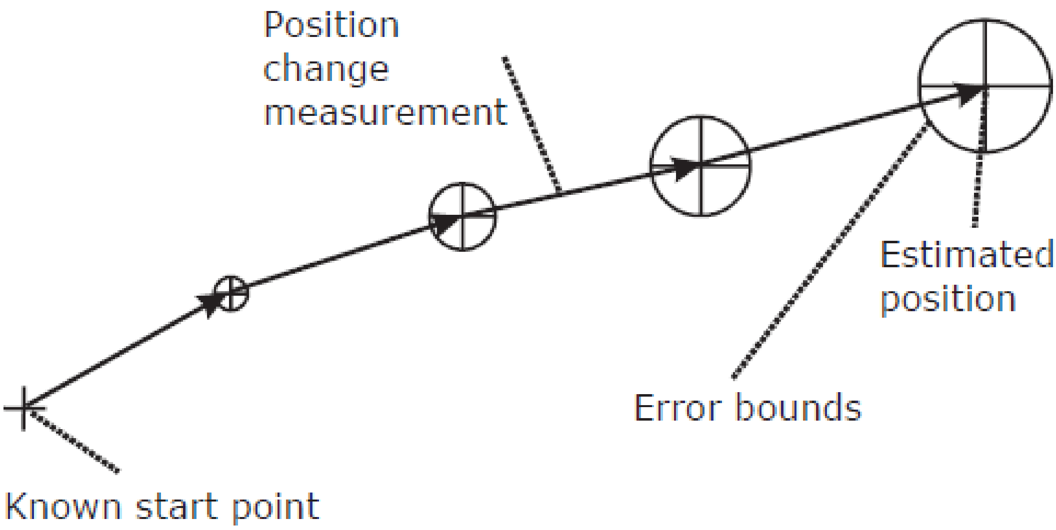


Figure 3.10: The DR method: the position estimate is obtained by updating an initial position using the course and distance traveled in that period. Since the method is relative, errors might accumulate unbounded [117].

For pedestrian navigation applications, MEMS-IMU data are used in two different ways to compute the navigation solution: INS and pedestrian dead reckoning (PDR) [28].

INS

The INS operates by continuously measuring the linear accelerations and angular velocities of a moving object by integrating raw data from accelerometers and gyroscopes. These measurements are integrated over time to compute changes in velocity, position, and orientation. While the system offers the advantage of being self-contained and independent of external signals, it requires sophisticated error correction and filtering techniques to mitigate the inherent drift and inaccuracies associated with sensor biases and noise

The operation of an INS involves several key steps to ensure accurate computation of position, velocity, and orientation. The following are the detailed steps involved in INS operation:

- **Sensor calibration:** Correct for sensor biases, scale factors, and misalignments and perform static and dynamic calibration procedures to establish baseline sensor performance. Continuously or periodically recalibrate to account for changes in sensor characteristics over time and varying operating conditions (temperature, aging).

- **Initialization:** Set the Initial Conditions by establishing the initial position, velocity, and orientation based on known starting conditions or external references (such as GPS).

- **Data acquisition:** Continuously measure linear accelerations and angular velocities using the IMU sensors.

- **Coordinate transformation:** This involves the transform accelerometer and gyroscope measurements from the body frame to the navigation frame using the current orientation. Rotation matrices or quaternions are used to perform the transformation based on the current orientation.

- **Velocity calculation:** Integrate the measured accelerations over time to compute changes in velocity. Then, subtract the gravitational acceleration from the measured acceleration to isolate actual motion-induced acceleration.

- **Orientation calculation:** Integrate the measured angular rates from the gyroscopes over time to determine changes in orientation (roll, pitch, yaw) and use the integrated angular rates to update the system's current orientation.

- **Error correction and filtering:** Apply techniques like bias estimation and correction to minimize errors due to sensor biases. Use filtering algorithms such as the Kalman filter to estimate and correct for random noise and drift, improving overall accuracy. Also, strategies to compensate for drift over time should be implemented, such as zero velocity updates (ZUPTs) or external references.

- **Output Generation:** Generate continuous output of position, velocity, and orientation based on the integrated data and corrected measurements. Navigation information can be provided to user interfaces or other applications for real-time usage.

PDR

PDR is proposed to reduce the accumulated navigation errors to improve pedestrian MEMS navigation performance. PDR has four critical procedures: step detection, step length estimation, heading estimation, and position calculation. These parameters are then used to set up a PDR mechanization equation to estimate the user's horizontal position. The following are the detailed steps involved in PDR operation:

- **Step detection:** Analyze data from accelerometers to detect distinctive patterns associated with walking or running steps. Some common methods, including peak detection algorithms or threshold-based approaches, are often used to detect steps by identifying significant changes in acceleration.

- **Step length estimation:** Estimate the length of each detected step. Step length estimation methods may be based on empirical models such as linear regression and neural network models, a statistical analysis such as time and frequency domain analysis of accelerometer data, or combining accelerometer and gyroscope data.

- **Heading estimation:** Heading estimation is the process of determining the direction of pedestrian movements. Gyroscope data can be used to track changes in orientation and estimate heading relative to the starting orientation. Magnetometer data can also provide absolute heading information with respect to magnetic north.

- **Position estimation:** The final stage is to estimate the user position using the step length and heading information. The current position of the pedestrian is calculated from the previously known position, step length information, and the heading from a step interval.

The advantage of INS is the ability to provide 3D position, velocity, and attitude. However, it suffers the demerit that navigation solution errors grow rapidly with time. Accelerometer and magnetometer readings are affected by interference issues and noise from the sensors, especially when they are indoors, and gyroscope measurements have a significant drift in determining heading over a short period [118, 119]. Typical filtering methods, which include Kalman or particle filters, are commonly used to correct these errors [99, 120]. On the other hand, when using PDR, navigation solution errors are proportional to the distance traveled and not to the time [121]. Also, PDR provides a more accurate position solution than INS, without other aiding sources, because it uses fewer integration calculations.

PDR solutions have become practical in people's daily use [121] because many handheld devices are equipped with inertial sensors. PDR works have also used units that assemble inertial sensors called IMUs. IMUs are mounted mainly on feet and legs [99]. The shoe-mounted setting has been the most popular research-wise, given that the mechanics involved in the walking process and the foot allow re-calibrations at every step by applying the Zero-velocity UPdate (ZUPT) method.

3.1.3.5 **Map-matching (MM)**

MM algorithms, also called map measurements, combine current positioning data with spatial map data to identify the correct link on which a pedestrian travels while improving positional accuracy. MM algorithms use prior knowledge of geographic characteristics to improve a target device's navigation solution by locating the target's absolute 2D or 3D coordinates inside the movement area. This process employs machine-learning algorithms, including pattern recognition/matching algorithms. The use of maps is an economical alternative to the installation of additional hardware.

3.2 Remote Pedestrian Localization Systems: A Systematic Review

In Section 3.1, we established a foundational understanding of localization and explored the current state-of-the-art techniques, measuring metrics, positioning methods, and technologies. Now, we focus on a more focused examination in Section 3.2.

This section presents an in-depth, state-of-the-art systematic review of the current outdoor remote pedestrian localization systems to identify their suitability for resource-constrained environments. This is followed by an account of the research methodology used to find the relevant articles and a description of the systematic review undertaken. The section concludes with the major findings of the systematic review and a brief discussion of them. By adhering to the PRISMA model's guidelines, we ensure our work is reproducible and replicable.

3.2.1 Brief Background and motivation

Aging population

The world's population is increasingly aging [2]. Globally, there were 727 million persons aged 65 years or over in 2020. Over the next three decades, the global number of older persons is projected to more than double, reaching over 1.5 billion in 2050. Old age comes with several non-communicable diseases such as cardiovascular diseases, hypertension, cancer, diabetes, and dementia [9].

Remote caregivers

As the number of elderly citizens increases, they are likely to represent an increased burden on the family, government, healthcare, and social services since many of them cannot live independently without assistance from a caregiver. Caregivers can be categorized into formal and informal categories. Formal caregivers are usually paid professionals or care service providers from institutions, including physicians, nurses, rehabilitation specialists, and personal support workers [122, 123]. Informal caregivers are, e.g., family members and relatives who care for a loved one requiring assistance. Due to the rapid increase in the aging population worldwide, the demand for formal and informal caregivers increases daily.

Sub-Saharan Africa's care for the elderly is predominantly a family-centered healthcare system. Families provide most long-term care without any organized training or support. This aging population, living in remote regions, has been exposed to the cruelest conditions in resource-constrained environments. Reliance on families alone to provide this care results in inconsistent care quality. It particularly puts a heavy burden on girls who are forced to drop out of school to look after the elderly [13]. Moreover, it may be unsustainable given the rapidly increasing number of older people living in rural areas and having their children living and working in distant urban areas, thus making it hard for them to visit frequently and consequently monitor and check on their health.

ICT solutions

ICT solutions can close the necessary resource gap to enable caregivers to provide the required care remotely. Technology is already playing a significant role in supporting caregivers, and most caregivers believe that technology can help them make caregiving more efficient, effective, safer, and less stressful through remote activity monitoring [124]. Remote monitoring, which is based on non-invasive, non-intrusive, and wearable sensors, actuators, and communication and information technologies, offers efficient solutions that bridge the gaps between healthcare and where elderly people really want to live every day [15].

Limited resources

Although many pedestrian localization systems have tried to reduce power consumption, they still assume that other types of resources are available, such as access to electricity to recharge the batteries, communication networks for exchanging data (Wi-Fi, Internet, cellular networks), service providers (coverage), and users with enough economic capacity and digital education to acquire and properly use these devices, as already explained in section 3.2.3. In other words, these systems are designed for developed countries, yet they are very necessary for less developed countries and rural areas with limited resources.

The main objective of this study was, therefore, to provide an in-depth, state-of-the-art systematic review of remote pedestrian localization systems with the aim of identifying if they are suitable for resource-constrained environments. For that, different localization algorithms, devices, technologies used for outdoor localization systems, and power-saving strategies were identified and analyzed. The outcomes of these analyses provided a clear view of the strengths and weaknesses of various localization systems when applied in resource-constrained environments. In addition, a description of what a resource-constrained environment was provided. Hence, it is a great research opportunity that seeks energy optimization strategies as a proposition for future research directions in localization systems suitable for elderly persons.

This study limited its scope to pedestrian remote location systems designed for outdoor environments, or at least both outdoors and indoors, published in the last decade (from 2012 to January 2023). That is, only indoor localization systems were discarded. This is because people in rural areas mainly live outdoors, working in primary industries such as agriculture, forestry, fishing, and hunting [35], including elderly people who spend most of their time outside their homes. Works that do not mention any power-saving strategy were excluded. Likewise, some types of localization systems that do not fit for pedestrian monitoring in resource-constrained environments, such as power-hungry hybrid systems using cameras or pure inertial localization systems, were also discarded.

The systematic review presented in this section is based on the PRISMA guidelines [125]. We identified, analyzed, classified, and discussed the current state of the art in terms of localization devices, techniques, and findings on localization systems reported in the scientific literature indexed in Scopus or Web of Science datasets. In summary, this section, therefore, focused on the following specific contributions:

(i) Systematically collecting and analyzing research works related to remote outdoor pedestrian localization systems.

(ii) Review the current state of the art in terms of localization devices, techniques, algorithms, and methods that consider the scarcity of resources, mainly power.

(iii) Identifying and describing the communication networks used.

(iv) Lastly, we give recommendations for the system(s) or combination of systems suitable for monitoring pedestrians in resource-constrained environments.

(v) Discussion of main challenges and future trends.

The remainder of this work in this section is structured as follows. Section 3.2.2 presents existing surveys on localization systems. Section 3.2.3 introduces the research methodology used to find the relevant articles and describes the systematic review undertaken. Section 3.2.4 presents the results from the systematic review. Section 3.2.5 briefly discusses the main findings, current challenges, and recommendations. Section 3.2.6 presents the conclusions of this review.

3.2.2 Existing surveys on localization systems

This section presents a review of the purpose and scope of existing surveys, showing how they do not sufficiently cover the peculiarities of resource-constrained environments. We could not find review papers specific to our area of interest, i.e., pedestrian localization systems for resource-constrained environments, so we decided to look at the reviews on pedestrian localization systems in general in the last ten years. Some reviews and surveys have been conducted about resource-constrained devices, but as explained in chapter 2, there is a difference between resource-constrained environments and resource-constrained devices.

Table 3.2 summarizes the comparison between the 35 survey papers on pedestrian localization from 2012. Most surveys comprehensively discussed localization system technologies, techniques, and methods. Additionally, some authors briefly discussed current challenges regarding indoor and outdoor localization technologies, techniques, environment, devices, coverage, and privacy. Even though it has been noted in the introduction that elderly people in rural areas spend most of their time outdoors, most of the review papers targeted indoor environments only, with only 18% covering indoor and outdoor environments.

As discussed in chapter 2, there is limited or no access to electricity in rural areas, though 62% of the review papers considered power optimization, and still, it is mainly about IoT devices, as none of the reviews looked at resource-constrained environments.

Furthermore, only 18% of the review papers considered cloud computing, which is emerging as the key platform for localization system data storage, computing, processing, and analytics due to its simplicity, availability, and scalability. Cloud computing helps prolong the tracking device's battery life by transferring all power-hungry activities to the cloud, a significant requirement for battery-powered devices operating in a resource-constrained place [21].

The cost of current localization systems is a significant barrier to their adoption in many environments and communities. Our review found that 77% of existing survey papers considered cost a requirement but did not clearly define its real face value in terms of money. This lack of clarity can lead to disparities in affordability, particularly in resource-constrained environments. Therefore, our findings underscore the need for more precise cost evaluations in future research.

Active localization entails a device attached to or carried by the target, and because of that, its size and weight can significantly affect the movement of the pedestrian being tracked. However, only 10% of the papers looked at those parameters.

In the reviews considered, 14% looked at the independence (autonomy) of the designed systems from the user. But as already discussed in chapter 2, digital literacy is lacking in those remote rural areas, so this requirement must be given attention; otherwise, it might lead to application failure.

Also, 62% of the reviews were done without a specific health focus, end-user, or application. Different applications have different requirements and constraints to consider when designing a positioning system.

Due to the inherent limitations of single-position estimation technology, it is essential to consider hybridization to provide a better position estimation in all environments. Hybrid systems, as more explained in section 3.1.2.3, are also crucial in prolonging the battery life of the user devices. Hybridization was considered by 47% of the existing reviews and mainly to improve localization accuracy rather than power efficiency, a significant challenge in the environments considered for this review.

In conclusion, while existing surveys provide a broad overview of pedestrian localization systems, they fall short of addressing the peculiarities of resource-constrained environments. Notably, while 35 surveys from the last decade were analyzed, none specifically targeted pedestrian localization in resource-constrained environments. Instead, they primarily focused on general localization technologies and methods, with a significant bias toward indoor environments, despite the noted importance of outdoor positioning for elderly people in rural areas. Future research

Table 3.2: Comparison of criteria included in existing surveys. HT: Hybrid Technologies; PC: Power Consumption; SW: Size & weight; CC: Cloud Computing; EES: Energy Efficiency Strategies; DL: Digital Literacy; ✓: Considered; ×: Not Considered

Article	Year	Scope	End-user or Application	HT	Scalability	Autonomy	Cost	Coverage	Accuracy	PC	SW	CC	EES	DL
[107]	2017	Indoor	General	✓	×	×	✓	✓	✓	×	×	×	×	×
[126]	2019	Indoor	General	×	✓	×	✓	✓	✓	✓	×	×	×	×
[127]	2018	Indoor	General	×	×	×	×	×	✓	×	×	×	×	×
[23]	2021	Outdoor	GNSS-Free	×	✓	✓	✓	✓	✓	✓	✓	✓	×	×
[94]	2019	Outdoor	General	×	×	×	✓	✓	×	✓	×	×	×	×
[128]	2020	Indoor	General	✓	✓	✓	✓	✓	✓	✓	×	✓	×	×
[129]	2017	Indoor	GNSS-free	×	×	✓	✓	✓	✓	✓	✓	×	×	×
[130]	2018	Indoor	Shopping Mart	×	×	×	✓	✓	✓	×	×	×	×	×
[131]	2020	Indoor	Multi-resident	×	✓	×	✓	×	✓	×	×	×	×	×
[132]	2020	Indoor	Health	✓	✓	×	×	✓	✓	×	×	×	×	×
[133]	2019	Indoor & Outdoor	Smart city	×	×	×	✓	✓	✓	✓	×	×	×	×
[134]	2018	Indoor & Outdoor	General	✓	×	×	✓	✓	✓	✓	×	✓	×	×
[54]	2019	Indoor	Pedestrian	✓	✓	×	✓	✓	✓	✓	×	✓	×	×
[135]	2019	Indoor	General	✓	×	×	✓	✓	✓	✓	×	✓	×	×
[65]	2021	Indoor	Pedestrian	✓	×	×	✓	×	✓	×	×	×	×	×
[90]	2018	Indoor & Outdoor	General	✓	✓	×	✓	✓	✓	✓	×	×	×	×
[136]	2022	Indoor	Health /Hospital	✓	✓	×	✓	✓	✓	✓	×	×	×	×
[86]	2017	Indoor	General	✓	✓	×	✓	✓	✓	×	×	×	×	×
[137]	2021	Indoor	General	✓	×	×	✓	×	✓	✓	×	×	×	×
[138]	2020	Indoor	Elderly	×	×	×	×	×	×	×	×	×	×	×
[20]	2023	Indoor & Outdoor	General	×	✓	✓	✓	✓	✓	✓	×	✓	×	×
[19]	2017	Indoor	Pedestrian	×	×	✓	×	✓	✓	✓	×	×	×	×
[139]	2014	Indoor	Smart homes	×	×	×	✓	×	✓	×	×	×	×	×
[140]	2016	Outdoor	General	×	×	×	×	×	✓	✓	×	×	×	×
[141]	2015	Outdoor	General	✓	×	×	×	✓	✓	×	×	×	×	×
[142]	2018	Indoor	General	✓	✓	×	✓	×	✓	✓	×	×	×	×
[143]	2017	Indoor	Emergency response	✓	✓	×	✓	✓	×	×	✓	×	×	×
[144]	2017	Indoor	General	✓	✓	×	✓	✓	✓	✓	×	×	×	×
[145]	2015	Indoor & Outdoor	General	×	✓	×	✓	×	✓	✓	×	×	×	×
[146]	2015	Indoor	General	×	×	×	×	×	✓	×	×	×	×	×
[147]	2016	Indoor	General	×	×	×	✓	✓	✓	✓	×	×	×	×
[148]	2016	Indoor & Outdoor	General	✓	×	×	×	×	✓	✓	×	×	×	×
[149]	2015	Indoor	General	×	✓	×	✓	×	✓	×	×	×	×	×
[150]	2015	Indoor	General	×	✓	×	✓	×	✓	✓	×	×	×	×
[97]	2022	Indoor$ Outdoor	General	×	✓	×	✓	✓	✓	✓	×	✓	×	×
Our Review		Indoor & Outdoor	Pedestrian	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

needs to focus more on outdoor environments, detailed cost evaluation, power efficiency through hybrid systems, and user-centric design to meet the specific needs of resource-constrained environments.

3.2.3 Research method

This section introduces the procedure and methodology for identifying studies relevant to this systematic literature review. The methodology has been selected for its straightforward procedure, which other researchers can easily reproduce, to comprehensively analyze the published research, identify current trends, and detect the unexplored research lines on a particular topic. As part of the systematic review, we used the PRISMA guidelines [125], consisting of a 27-item checklist together with a flow diagram divided into four parts (identification, screening, eligibility, and included). This section updates the key findings of the published systematic review [26] by referencing research articles published between 2012 and January 2023.

A) Research questions

Setting the right research questions is a crucial stage of any systematic review, as it is paramount to identify the analysis's main objectives. We conducted this review with the following main research question (MRQ):

Are current pedestrian localization systems suitable for resource-constrained environments?

This main question is generic; therefore, we broke it down into the following specific research questions (RQ):

RQ1: What are the resource optimization strategies currently used by the localization systems? The question will help us to identify the technologies, algorithms, and strategies used to save resources, and power will be the main resource we will focus on.

RQ2: What communication technologies are used by the current localization systems? The question will help us understand the communication technologies required for remote localization systems, including coverage areas, data capacities, and limitations of various networks.

RQ3: What are the current position estimate technologies and algorithms used? This research question will allow us to identify the positioning technologies and algorithms, the computing environment (on the edge/the Cloud), accuracy, and position update rate for the systems operating in those environments.

RQ4: How are the devices used in pedestrian localization systems? This research question will help us identify the main characteristics of the user device: mounting point, size, included sensors, commercial or custom-made, and cost.

B) Keywords

Research studies on indoor and outdoor positioning have increased exponentially over the years, with more applications requiring localization services. So, it's essential to define clear search queries and strategies to find the most relevant publications related to the topic of this systematic review. Therefore, we proceeded to identify keywords related to the research topic and its objectives. The keywords were chosen according to the infrastructure, user, and application. As mentioned in RQ1, power is the main resource being considered in this review since it is a significant challenge for the environments we are considering.

Under application, we used keywords tracking, positioning, monitoring, geolocation, and monitoring since they are closely associated with localization, and some authors use them interchangeably. Under the users, we also considered the wildlife keyword since wild animals also live in constrained environments or isolated and remote areas, places requiring the designers of the localization system for the animals in those environments to take into consideration the same challenges mentioned above in chapter 2.
Table 3.3 showcases the meticulously chosen keywords that were pivotal in our research process. The wildcard pattern (* in the queries) was introduced to identify related concepts with the same prefix (e.g., position, positioning, positions, etc.), thereby ensuring a comprehensive search.

Table 3.3: Keywords related to the topic research.

Keywords Infrastructure	Keywords User	Keywords Application
Low-power	Pedestrian	Position*
	Wildlife	Tracking
	Dementia	Localization
	Elderly	Geolocation
	Vulnerable	Location
		Monitor*

Table 3.4: Lists of electronic databases searched.

Electronic Database	URL
Web of Science	`https://www.webofscience.com/`
Scopus	`https://www.scopus.com/`

C) Query

Once keywords are defined, a rigorous study selection process is carried out by first defining relevant search queries and running them against scientific digital libraries (Scopus and Web of Science in this work) to identify all potentially relevant studies. Table 3.4 shows the URL and lists of electronic databases searched, and Table 3.5 shows the search queries used. Although the term 'localization' or 'positioning' has been used for a long time, and outdoor and indoor positioning has been studied for many years, we limited this review to articles published in the last ten years (from 2012 to January 2023). We think ten years is enough as technology has greatly changed compared to the early 1990s and 2000s. For example, there have been great changes in smartphones and satellite technology in recent years.

D) Study selection

The selection of relevant articles was meticulously conducted, adhering to the PRISMA process for study selection. This crucial step involves identifying studies that address the research questions, eliminating duplicate records, and establishing inclusion and exclusion criteria. These criteria serve as the

Table 3.5: Scopus and Web of Science search queries.

Database	**Input Query**	**No of Articles**
Web of Science	TS = (((pedestrian OR elderly OR vulnerable OR dementia OR wildlife) AND (localization OR location* OR geolocation OR tracking OR monitor* OR position*) AND (low-power))) Timespan: 2012-January 2023	472
Scopus	TITLE-ABS-KEY ((pedestrian OR elderly OR vulnerable OR dementia OR wildlife) AND (localization OR location OR geolocation OR tracking OR monitor* OR position*) AND (low-power))	460

foundation for the final decision on which works are included in the qualitative and quantitative synthesis, thereby ensuring the rigor and reliability of this review.

i) Stage 1: Identification
Scopus and Web of Science are pivotal databases, which index works from various sources like IEEExplore SpringerLink, Elsevier, Wiley Online Library, etc. The results from all datasets are merged, leading to the identification and removal of duplicate records. The retrieved records and their abstracts, titles, bibliographies, and metadata are imported in CSV format and stored in MS Excel software. This software, with its capabilities to remove duplicates and classify and analyze the studies obtained from search engines, significantly enhances the efficiency and accuracy of the review process.

ii) Stage 2: Screening and Selection criteria
Once we have removed duplicate records, we obtain 640 unique registries, which must be filtered to obtain only relevant publications for this review. Thus, we defined the following inclusion criteria (IC) and exclusion criteria (EC).

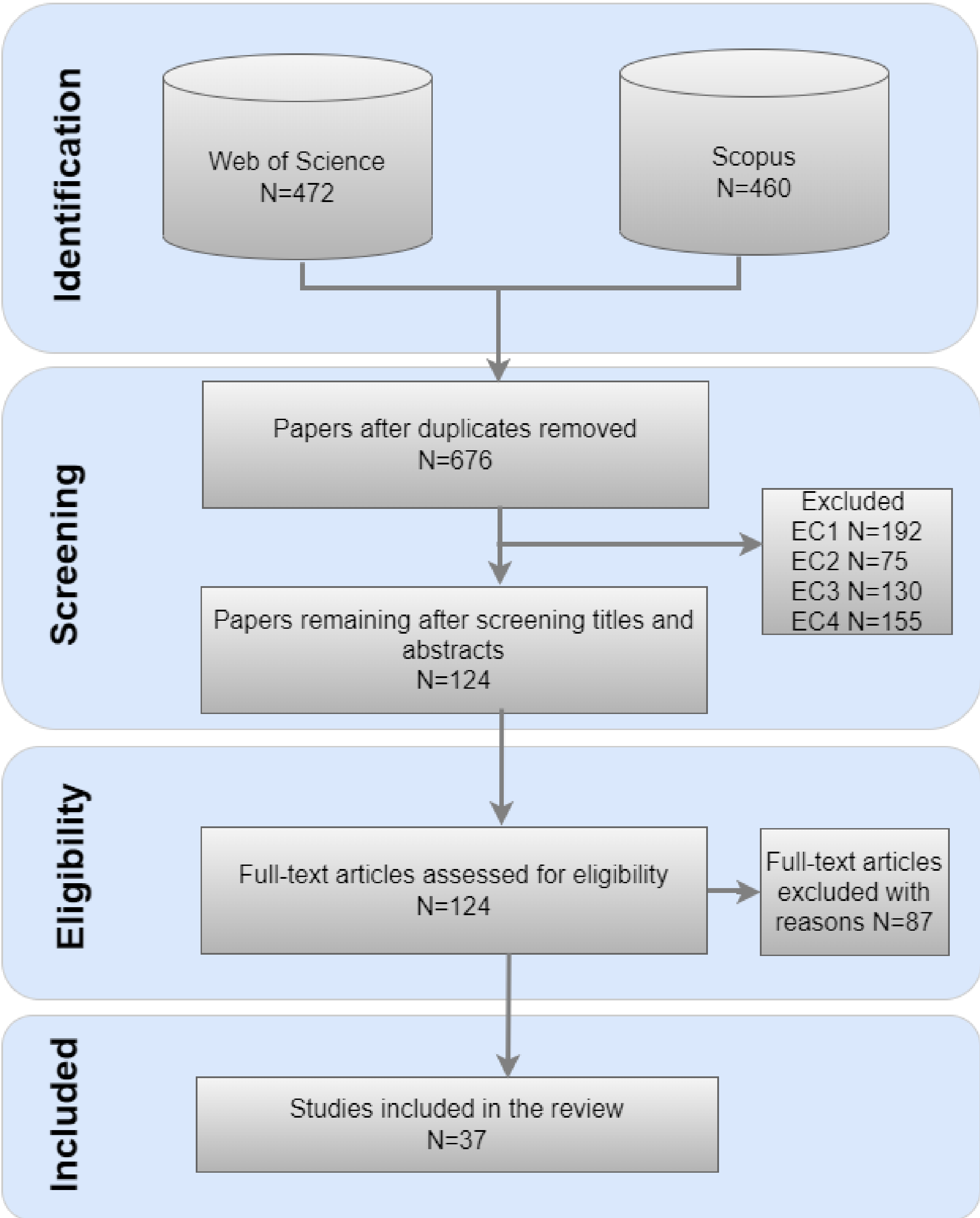


Figure 3.11: PRISMA Flow Diagram.

Inclusion criteria.

IC1: Research works written in English.

IC2: Each article must be related to the localization of pedestrians or wildlife.

Exclusion criteria.

EC1: Research works that do not mention anything about energy consumption, low consumption, low power, low resources, or similar.

EC2: Works where cameras are used as part of the localization system.

EC3: Works where only INS is used as part of the localization system.

EC4: Research works proposing systems valid only for indoor environments.

A meticulous manual revision of titles and abstracts was carried out to ensure that only works that meet all the requirements established in the IC and EC were selected. This was followed by tagging the articles as ACCEPTED for those that met the criteria and REJECTED for those that did not. This rigorous process resulted in the selection of approximately 24% of the total studies obtained in the previous stage, thereby ensuring the thoroughness and precision of this review.

iii) Stage 3: Eligibility

In this stage, we carefully read each remaining study, considering the main objective of this review and the established IC and EC. If the article reviewed meets the requirements established in previous steps, it is included in this work.

iv) Stage 4: Included

The studies are categorized according to their conclusions and contributions to the research field (localization systems in resource-constrained environments). This step is the last filter to select only relevant publications for this review.

E) Main Figures for the PRISMA Process in the Current Review

Figure 3.11 shows the flow diagram and the results after following the process. Through an extensive article search performed using search engines from two curated scientific digital libraries, Scopus and Web of Science, using an equivalent search query, we identified 932 potentially relevant studies concerning the research questions. We identified 460 from Scopus and 472 from Web of Science. When the screening process was carried out, by first removing duplicates, we remained with 640 unique works. We subsequently screened the remaining articles' titles, abstracts, and keywords against the inclusion and exclusion criteria; 124 articles remained. Finally, the remaining works were checked against the eligibility criteria in the eligibility phase to obtain a final set of included articles. We included only 37 articles in our review for the complete analysis, and this represents about 5% of the initial number.

F) Overview of the selected studies
Although the search queries provided 932 works, only 37 fulfilled all the criteria established in this work and were analyzed (see Figure 3.11). The distribution over the years of the selected works is shown in Figure 3.12, where the type of article is also differentiated.

G) Data extraction
During this process, we collected all the relevant information from the 37 selected studies. This information includes resource optimization strategies currently used by the localization systems (RQ1), communication technologies and networks used (RQ2), position estimate technologies and algorithms used (RQ3), and how the devices are used in pedestrian Localization systems (RQ4). The main outputs of this process are reflected in Section 3.2.4.

3.2.4 Results

This section will analyze the key information extracted from the 37 selected studies to answer the four defined research questions.

3.2.4.1 Communication technologies

Most remote energy-efficient localization technologies require exchanging data with a network to determine the device's position from the cloud. In this review, different authors have used different communication technologies to minimize power consumption and lower costs. This section provides a brief overview of those communication technologies. Table 3.6 gives a summary of some of the properties

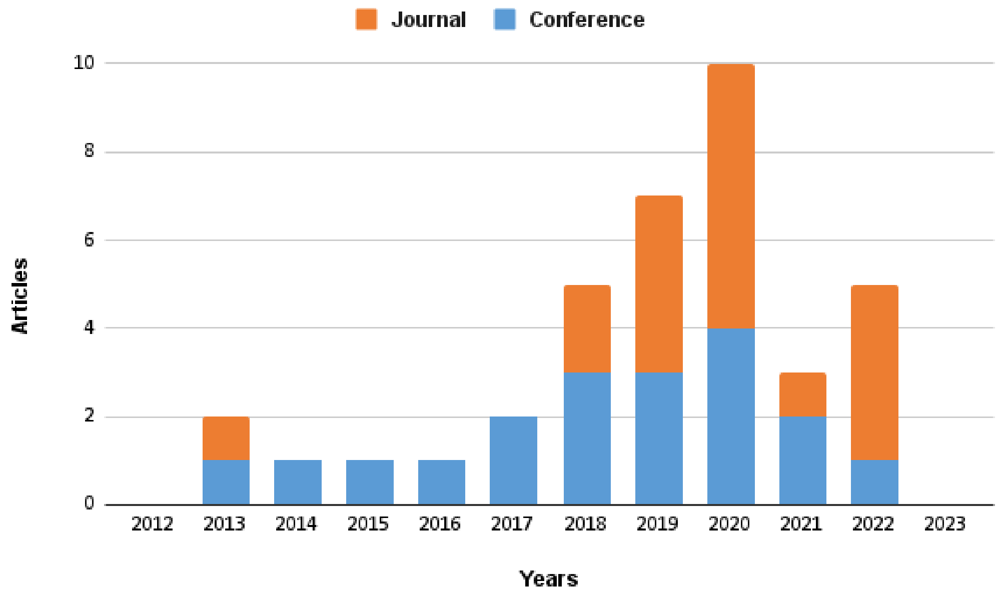


Figure 3.12: Distribution of the articles considered in this review over the years, grouped by publication type.

of communication technologies considered in this review, and these include data rates, bandwidth, energy consumption, and range.

A) Cellular networks

Cellular networks operate on different frequency bands, including the 0.9, 1.8, and 2.8 GHz bands. They are based on open, global industry standards, use licensed spectrum, and are always operated by wireless network providers. Cellular networks offer high bandwidths, low latency, high reliability, and good coverage [65]. However, they are not suitable for energy-constrained devices. Because of that, the GSMA has introduced two additional LTE standards: NB-IoT and LTE-M. Even though NB-IoT and LTE-M are primarily designed for LPWAN use cases to provide moderate energy efficiency, the rollout of these networks is still in its early stages, with patchy or no coverage in many regions.

Research studies in [33, 61, 100, 151, 152, 153] used cellular networks as the communication network, which represent 18% of the reviewed papers. All the

Table 3.6: Comparison of RF communication networks used in this literature review.

	Sigfox	**NB-IoT**	**LoRaWAN**	**WiFi**	**ZigBee**	**Bluetooth**
Standards	Sigfox	3GPP	LoRa Alliance	IEEE 802.11	IEEE 802.154	Bluetooth SIG
Modulation	BPSK	QPSK	CSS	DSSS, OFDM	DSSS, QPSK	GFSK
Frequencies	ISM:433MHz, 866MHz, 915MHz	Licensed under LTE	ISM:433MHz, 866MHz, 915MHz	ISM:2.4GHz, 5GHz	ISM:868MHz, 2.4MHz	2.4GHz
Coverage	10-40Km	1-10Km	5-15Km	10-100m	10-100m	10-100m
Bandwidth	100Hz	200Hz	125KHz, 250KHz	20MHz,40MHz, 80MHz,160MHz	2MHz	1MHZ
TX Limit	140 Packets per day	Unlimited	Duty Cycle Limit	Unlimited	Unlimited	Unlimited
Max Data Rate	100bps	200kbps	50kbps	Gbps	250kbps	2Mbps
Private Deployment	No	No	Yes	Yes	Yes	Yes
Energy Consumption	Extremely Low	Very Low	Extremely Low	High	Low	Low
Security	Low	High	High	Low-High	High	Low-High

studies used GSM networks, which are pervasively available in most countries but have high energy consumption. GSM networks have cell sizes of up to 35 km, and GSM far outreaches the coverage of WLAN and WPAN [48].

B) LPWAN

LPWAN technologies include LTE-M, NB-IoT, Sigfox, and LoRaWAN. LTE-M technologies were not used in any of the studies in this review. LPWAN is increasingly gaining popularity in industrial and research communities because of its low power, long-range, and low-cost communication characteristics. It provides long-range communication up to 10–40km in rural and 1–5km in urban zones [154]. In addition, it is highly energy-efficient (i.e., 10+ years of battery life) and inexpensive, with the cost of a radio chipset being less than $2 and an operating cost of $1 per device per year [92].

These promising aspects of LPWAN have prompted recent experimental studies on the performance of LPWAN in outdoor and indoor environments, as seen in this review (more than 70%). These properties make the LPWAN technology a perfect candidate for resource-constrained environments.

Many factors should be considered when choosing the appropriate LPWAN technology for application, including quality of service (QoS), battery life, latency, scalability, payload length, coverage, range, deployment, and cost. The respective advantages of Sigfox, LoRa, and NB-IoT in terms of IoT factors are demonstrated in Figure 3.13 and briefly explained in the following paragraphs.

Sigfox, LoRaWAN, and NB-IoT end devices are in sleep mode most of the time outside operation, which reduces the amount of consumed energy, i.e., long end-devices lifetime. However, the NB-IoT end device consumes additional energy because of synchronous communication and QoS handling, and its OFDM/FDMA access modes require more peak current [92]. This additional energy consumption reduces the NB-IoT end-device lifetime compared to Sigfox and LoRaWAN. NB-IoT offers the advantage of low latency. Owing to QoS and cost tradeoff, NB-IoT is preferred for applications that require guaranteed quality of service, and in contrast, applications that do not have this constraint should choose LoRaWAN or Sigfox.

The significant utilization advantage of Sigfox is that an entire city or village can be covered by one base station (i.e., range > 40 km). By contrast, LoRaWAN has a lower range (i.e., range < 20 km), and NB-IoT has the lowest range and coverage capabilities (i.e., range < 10 km).

Regarding payload length, NB-IoT allows data to be transmitted up to 1600 bytes, while LoRaWAN allows a maximum of 243 bytes. Sigfox proposes the lowest payload length of 12 bytes, limiting its utilization on various applications that need to send large data sizes. In addition, the deployment of NB-IoT is limited to LTE base stations. Thus, it is not suitable for rural or suburban regions that do not benefit from LTE coverage.

The NB-IoT specifications were released in June 2016; thus, the number of commercial applications has been limited to now. However, the LoRaWAN and Sigfox ecosystems are mature and are now under commercialization in various countries and cities. LoRaWAN can be deployed in 42 countries versus 31 countries for Sigfox [155]. In addition, one significant advantage of the LoRaWAN ecosystem is that it is available in Africa.

In summary, Figure 3.13 shows a clear difference in performance between licensed and unlicensed technologies. The licensed technology (NB-IoT) offers better QoS, payload length, latency performance, and scalability than unlicensed (LoRaWAN, Sigfox). Unlicensed technologies are cheaper, with a better coverage range and battery life.

From the cost aspects in terms of the spectrum (license), network/deployment, and end-device, Sigfox, and LoRaWAN are more cost-effective than NB-IoT, as shown in Table 3.7. In the following, Sigfox, LoRaWAN, and NB-IoT are discussed in terms of their technical aspects in regard to this review.

i) Sigfox

Sigfox is an LPWAN network operator that offers an end-to-end connectivity solution based on its patented technologies. Sigfox deploys its proprietary base stations equipped with cognitive software-defined radios and connects them to the back-end servers using an IP-based network [92].

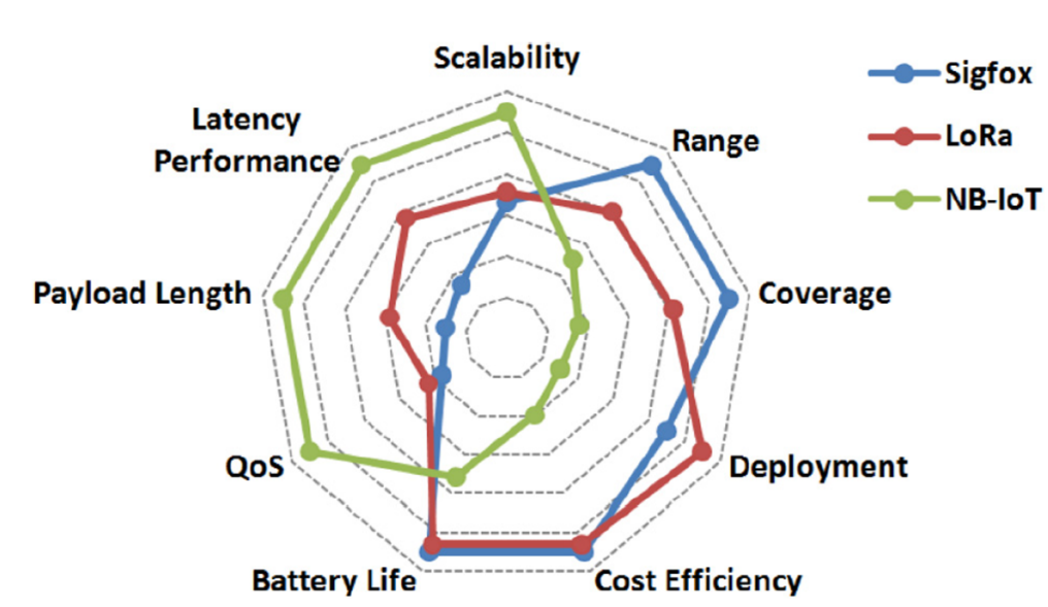


Figure 3.13: Respective advantages of Sigfox, LoRa, and NB-IoT in terms of IoT factors [90].

Table 3.7: Different costs for LoRaWAN, NB-IoT, and Sigfox [92].

Communication Network	**Spectrum cost**	**Deployment cost**	**End-device cost**
LoRaWAN	Free	>$100/gateway >$1000/base station	>$20
NB-IoT	>$500 M /MHz	>$15000/base station	$3-$5
Sigfox	Free	>$4000/base station	<$2

Sigfox uses unlicensed ISM bands, such as 868 MHz in Europe, 915 MHz in North America, and 433 MHz in Asia. However, it's a closed network and is not available without permission from the network service provider. Sigfox services are currently not operational in Africa.

Sigfox uses the frequency bandwidth efficiently and experiences very low noise levels, leading to very low power consumption, high receiver sensitivity, and low-cost antenna design at the expense of a maximum throughput of only 100 bps. The number of messages sent over the uplink is limited to 140 messages (twelve bytes each) and four downlink messages (eight bytes each)per day [59].

Sigfox can communicate over ranges of up to 10km in urban areas and up to 50km in rural areas. In this review, Sigfox was used in three studies [34, 52, 156]. For example, authors in [156] ran an experiment on an LPWAN tracking platform based on Sigfox and achieved a maximum range of 20km.

ii) LoRaWAN

LoRaWAN is a physical layer technology that modulates the signals in the sub-GHz ISM band. LoRaWAN provides for long-range communications: up to three miles (5km) in urban areas and up to 10 miles (15km) or more in rural areas under LoS circumstances. A key characteristic of the LoRaWAN-based solutions is ultra-low power requirements, which allow for the creation of battery-operated devices that can last for up to 10 years [157].

Bidirectional communication is provided by the chirp spread spectrum (CSS) modulation that spreads a narrow-band signal over a wider channel bandwidth. The resulting signal has low noise levels, enabling high interference resilience, and is difficult to detect or jam.

LoRaWAN uses six spreading factors (SF7 to SF12) to adapt the data rate and range tradeoff. The spreading factors of a LoRaWAN signal affect the energy consumption, required airtime, maximal payload size, and the achievable communication range of transmission [59, 121] as shown in Figure 3.14. For example, a higher spreading factor allows a longer range at a lower data rate expense and vice versa. The LoRaWAN data rate is between 300bps and 50kbps, depending on the spreading factor and channel bandwidth [23, 59].

The authors in [16, 22, 24, 52, 71, 73, 76, 103, 116, 156, 157, 158, 159, 160, 161, 162, 163, 164, 165, 166, 167, 168] used LoRaWAN as a communication network representing 64% of all the studies in this review. For example, [62] developed a wildlife monitoring system leveraging BLE and LoRa. The range

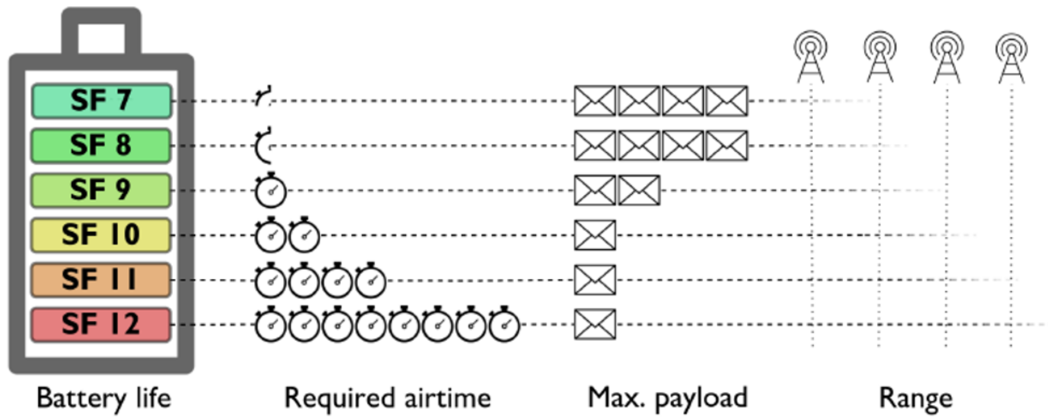


Figure 3.14: The SF of a LoRa signal affects the energy consumption, required airtime, maximal payload size, and the achievable communication range of a transmission [59].

from transmitter at a transmit power of 4dBm, BW of 125 KHz, and SF of 12 under a flat rural environment (open field) was 15.7 km. From the experiment, high transmission power results in higher received signal strength, increasing the reception range.

iii) NB-IoT

Narrow Band IoT (NB-IoT) was introduced by the 3rd Generation Partnership Project (3GPP) in 2016 [90, 155]. Unlike Sigfox and LoRaWAN, NB-IoT operates in licensed spectrum and synchronous communication. Therefore, it provides higher traffic reliability and is preferred for IoT systems that need guaranteed QoS. The NB-IoT communication protocol is based on LTE, and its power consumption can be reduced by reducing LTE protocol functionalities.

It has a frequency bandwidth of 200 KHz and uses OFDMA for downlink and SC-FDMA implemented for uplink communication. It has a 250 kbps data rate for downlink and a 20 kbps data rate for uplink.

One of the main advantages of this standard is its compatibility with traditional cellular networks. Therefore, it can work in LTE or GSM under licensed frequency bands. In this review, NB-IoT was used in two studies [16, 169] and only for communication.

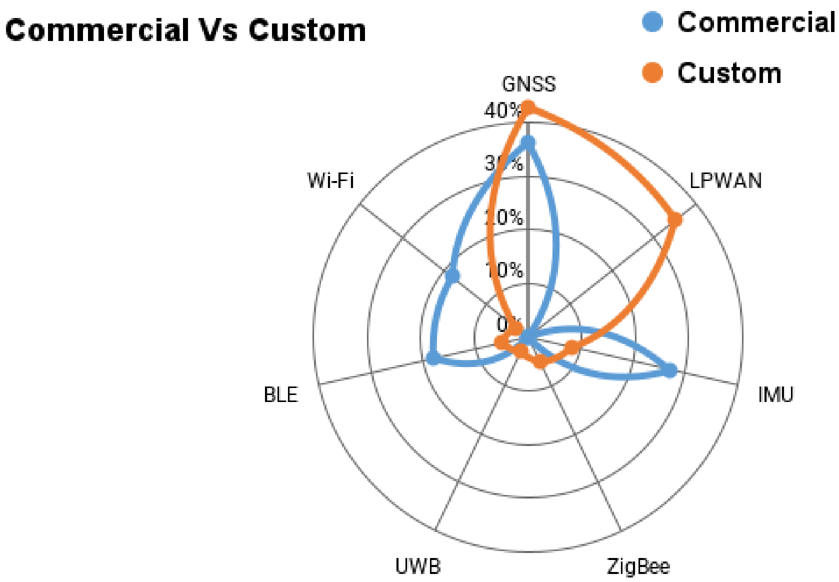


Figure 3.15: The spider graph shows the comparison of the different devices used in the commercial and custom systems.

C) WLAN (Wi-Fi) Communication technologies

Wi-Fi technology is a tempting approach since Wi-Fi access points are readily available in many environments. However, this is not the case for resource-constrained environments. The range can be scaled up to 1km, which Wi-Fi typically covers outreaches that of Bluetooth or UWB, and another advantage of using Wi-Fi is that LoS is not required. In this review, Wi-Fi [100, 170, 171] was used in only three studies as a communication network.

D) WPAN Communication technologies

WPAN solutions such as BLE, ZigBee, and UWB provide short and medium-range communications and signal-range coverage of up to 300 m in free space. In this review, BLE and UWB were used for communication by authors in [62] and [70, 99], respectively. Since ZigBee and BLE operate in unlicensed ISM bands, they are vulnerable to interference from a wide range of signal types using the same frequency, which can disrupt radio communication.

For example [62], developed a wildlife monitoring system leveraging BLE and LoRaWAN. The range from transmitter under a flat rural environment (open field) was up to 200 m for BLE.

3.2.4.2 Characteristics of user devices

User devices were used to perform different functionalities, including data collection, data transmission, and localization. The main focus of our characterization is to show external usability attributes associated with the use of specific user devices. These include the mounting point, cost, size, and weight. The study also identifies user devices that are commonly used together and whether they are commercial or custom-made.

i) Commercial or Custom device

   In this review, commercial devices represent only 18% of the user devices used by different authors, and all are smartphones. 82% of the reviewed work used custom devices. Arduino and Raspberry Pi account for 25% and 11%, respectively, of the development boards and platforms used to build custom systems. 50% of the reviewed work gives a partial description of the development platforms used, with 14% not giving any description of the platforms or boards used to develop the systems they used to conduct their experiments. Not knowing the platforms used to make their systems makes it hard to replicate and validate the results. The use of custom devices is attributed to the need for tailored solutions that require technologies like LoRaWAN and combinations (hybridization) such as GNSS + LoRaWAN, which commercial devices do not usually provide.

In Figure 3.15, a descriptive analysis of existing commercial and custom devices is derived as follows: 18% of the commercial devices include Wi-Fi technology, while only 3% of the custom made include it. Similarly, BLE is included in 18% of commercial devices and 66% of custom-made devices. This phenomenon, where a commercial device's existence is more prominent compared to its custom device usage, is also true for GNSS and IMU. The implication is that there may be no need for developing custom devices using such technologies. On the contrary, technologies such as LoRaWAN and UWB are not prominent in commercial devices. Our study results show 0% for both technologies under commercial devices and 33% and 3% for custom devices, respectively. This trend shows that there is a need for further development and testing of these technologies in the custom setting before the commercialization takeoff.

ii) Common sensors used

Overall, 56% of the studies in this review used GNSS sensors [16]-[22]. GPS receivers were the most used type of GNSS constellation at 70%, with 30% using multi-constellation receivers covering GPS, GLONASS, and Galileo on a single chip. LPWAN technologies are increasingly gaining popularity in industrial and research communities because of ultra-low power, low cost, and long-range properties. In this review, LPWAN technologies were used for both localization and communication. 33% of the studies in this review [22, 24, 52, 73, 103, 116, 156, 158, 159, 160, 166, 168, 170] used the LPWAN technologies for localization and 64% for communication purposes. LoRaWAN [22, 24, 52, 73, 103, 116, 158, 159, 160, 166, 168, 170] was the most preferred for both localization and communication because it uses open standards and also operates in Africa in relation to Sigfox [52, 156], and was used in only two papers. WPAN technologies were used in 21% of the reviewed studies. The WPAN technology included BLE sensors [61, 62, 165, 170], UWB [71] and ZigBee [70, 172].

INS systems, which commonly integrate sensors such as accelerometers, gyroscopes, magnetometers, and barometers, were used in 18% of the studies [99, 103, 153, 157, 165, 171]. These navigation sensors were used only to complement other technologies such as GNSS [99, 103, 153, 157, 165, 171] or Wi-Fi [171] as stated in **EC3**. This is because of the progressive accumulation of errors over a period of time during motion, and it also gives a relative position.

WLAN devices [100, 153, 171] were used in 9% of the works reviewed for localization and communication purposes. The authors who used Wi-Fi leveraged the existing infrastructures, and these do not exist in resource-constrained environments, thus limiting the adaption of the technology.

Hybrid systems were used in 33% of the studies, and the most popular combinations of hardware found in the literature were GNSS with INS [99, 153, 157, 165, 171].

iii) Mounting points

Whereas the mounting point has an effect on the performance of the localization system, only 40% of the reviewed studies mentioned the mounting points used. All authors who used commercial devices mentioned the mounting points. Commercial devices come with already designed and packaged morphology that makes them restrictive and easy for it's designed for mounting points. Even though the authors who used custom devices had an opportunity to redesign and meet the targeted points as identified from different mounting points adopted, only 26% mentioned their mounting points. The most common mounting points for commercial devices were hands [153, 171], pockets [103], bracelets [170], and clothes [61, 99], but in addition to these mounting points, the authors who used custom devices explored different points like a collar [62, 160, 163, 172], animal ear [167] and walking sticks [73]. Not knowing the mounting points makes the adoption of these systems challenging, especially with the group of people and environment being dealt with. It also makes it hard to replicate the system and validate the results.

iv) Size and Weight

Although the size and weight of a user device are essential requirements for tracking systems, only 10% of studies reviewed mention the size and weight of the systems used in their experiments. Tracking applications, in particular, are constrained by size and weight, limiting the range of species that can be tagged. The authors in [34, 172] give a thorough explanation of the total size and weight of their developed system. For example, the authors in [172] suggested that a tracking device placed on an animal should ideally be less than 5% of the animal's body mass. Even though their study was done on animals, size and weight have a similar constraint on the choice of

Table 3.8: Different costs and weights of the devices.

Tech	Spectrum cost	Deployment cost	End-device cost	Weight
Sigfox	Free	$>$ $4000/base station	<$2	<100g
LoRa	Free	>$100/gateway, >$1000/base station	$3-$5	$<$ 200g
NB-IoT	>$500M/MHz	>$15000/base station	>$20	<100g
BLE	Free	$5–$30 per tag	$\sim$ $5 receiver-/reader	<100g
UWB	Free	>$45 per tag; >$290 per anchor	Expensive laboratory equipment	$>$ 100g
Wi-Fi	Free	$20–(more than $50) per Access Point	$>$ $10	50g-200g
GNSS	Not free but already defined	Billions of Pounds (but already existing)	$1-$100	<100g
INS	Free	$> \$10 * n$	$10-$100	$<$ 100g

tracking application to adapt for pedestrians as well. The authors in [34, 167] designed small, lightweight, low-power electronic tracking tags of 2.6 g and 30 g total weights, respectively, which is far less than the average weight of a smartphone today. On average, a phone weighs around 200 g.

v) Cost

The cost of the user devices or systems used is very important since we are looking at resource-constrained environments, as explained in section 2.1. Even though our literature search was biased toward systems designed for constrained environments, only 40% of the reviewed studies considered the cost of their designed systems as an essential requirement. Costs were minimized by using low-cost hardware, architecture designs, technologies, and algorithms, as well as utilizing the already existing infrastructures. The cost of a smartphone with localization capabilities is approximately $200 or more. Most designed custom user devices are estimated to cost $100-$500. Though for both cases, these costs cover the user device, there is an assumption of existing infrastructure on which these devices operate, such as Wi-Fi, satellites, cellular networks, and the Internet. Table 3.8 represents the summary of technologies, cost, and weight descriptions.

3.2.5 Discussion and Recommendations

In this section, we will discuss the problems and limitations of current localization systems and examine alternative techniques and technologies not considered in the literature that might impact resource-constrained systems.

3.2.5.1 Suitability of current monitoring tools

The current localization and positioning systems as they are or as they were conceived are not suitable for a resource-constrained environment because of the following reasons:

i) High power consumption of the main localization technology: GNSS
Location estimation has been successfully implemented in outdoor environments using GNSS technology. This is clearly manifested in this review, as more than 50% of the reviewed work used GNSS for localization. It may not be the best solution as per the use case in this review for the following reasons.

    a) The relatively high energy consumption of the technology aligns poorly with the stringent constraints of battery-powered devices. Different power optimization strategies employed by different authors will be presented in section 4.1 to mitigate some of the related power challenges. For example, the authors in [16, 33, 34, 100] perform the location estimation from the cloud instead of the device. This solution greatly reduces energy consumption but requires stable and reliable communication networks and the Internet for exchanging data, resources very scarce in constrained environments.

b) The time to first fix (which is a measure of time required to obtain satellite signals and produce a valid coordinate within a specific performance [28]) of a GNSS receiver plays an essential role in the magnitude of this additional energy consumption and must, therefore be considered when designing a GNSS- based low power localization system [173]. So, as the authors implemented duty cycling, update rate, and sampling rate solutions, a good trade-off was supposed to be made to minimize the overall power consumption, something that had not been discussed in any of the works.

   Multiple new techniques exist to overcome this challenge, such as extended and autonomous ephemeris prediction and assisted GPS (AGPS), which dramatically improve the TTFF [77]. Still, most require Internet or GSM connectivity and a communication channel such as LTE and NB-IoT with sufficient capacity and data rate not available in resource-constrained environments. AGPS systems do not work in remote areas where mobile networks do not provide coverage [28].

   Using multi-constellation can increase the number of satellites in the view and greatly affect the TTFF duration. Also, if a receiver can track and use multiple signals (multi-frequency), the convergence time to get positioning and heading (dual-antenna receivers) is decreased to several seconds [174]. We propose that further research be done to assess the effect of using multi-constellation and multi-frequency receivers to reduce the TTFF versus the overall energy consumption.

ii) Required high-capacity communication networks
This review is biased toward remote monitoring and localization tools and systems, so there will always be a need to connect with a server (cloud). This explains the need for a communication network with low power, long-range, and stable connections. Some authors used communication networks such as cellular networks [33, 61, 100, 151, 152, 153] and Wi-Fi [100, 170, 171], which have high power consumption and also do not exist in the environments discussed in this review. The authors also used short-range communication

networks such as Bluetooth [62] and UWB [70, 99] for data exchange. However, depending on the application requirements, these technologies may not be suited for outdoor localization systems or those covering large areas.

iii) The localization accuracy of LPWAN is not good enough for pedestrian monitoring.
LPWAN technologies were used for localization in 38% of all the reviewed works. LPWANs offer the best power consumption and long-range coverage solutions, but the accuracy achieved is not suitable for pedestrian monitoring, more so for the elderly with dementia. For example, authors in [52] suggest that GNSS receivers be only omitted in favor of LPWANs when an error of more than 100m is acceptable, and the energy budget is extremely constrained. The suggestion is supported by the experiment they conducted, which achieved an accuracy of 214.58m for the rural Sigfox and 398.40m for the urban LoRaWAN dataset in an area of around 52.97 km2. We acknowledge that authors in [73, 159] achieved low accuracies ranging below 50m using LPWANs. But for all the cases, small open ranges of 200m and less were considered for the experiments, which are not typical of rural areas where elderly people move freely. Therefore, we argue that the LoRaWAN localization in real-life conditions is ineffective, as the estimation of the distance between the node and the gateway changes heavily depending on the location of the node and radio channel attenuation. When little is known about the node placement, as in most cases, and the signal is subject to interferences due to the use of unlicensed bands, the LoRaWAN positioning provides very low precision in hundreds of meters.

iv) Low-cost but not affordable
Localization sensors and systems are now readily available for personalized use and have been trending for quite some time in developed countries. The rate at which such platforms have been adopted is lower in low-developed countries and rural areas. Affordability (cost) is one of the factors that contribute to these low adoption rates. From the review, we found that most designed user devices or systems (custom and commercial) are estimated to cost 100-500 less the infrastructure cost. As explained in section 2.1, users

can not buy these existing localization systems with poverty levels in their areas. This explains why such systems have thus far had minimal influence and adaption in rural environments such as the one described in this review.

v) Many proposed systems have not been validated in the wild
Evaluation is done over simulations in some of the reviewed works [16, 62, 151] because it does not require deploying expensive hardware and manual labor. Although some simulated environments are able to mimic the real world, a comprehensive empirical evaluation is needed to demonstrate the feasibility of the proposed solution in realistic conditions. We further note that even for those not simulated, they were designed and tested in labs, and there is no proof that real users were involved in developing and validating these systems. It is very important to make your users feel like they are involved and valued in the system's initiatives through co-creation and co-design. This greatly impacts user experience, trust, awareness, and acceptance.

vi) Replicability
It is very important that research can be replicated. This means that other researchers can test the findings of the research and make recommendations. Replicability keeps researchers honest and can give readers confidence in research. Many authors in this review do not provide enough details about the methods used, making reproducibility of suitable devices and systems for the right environment challenging.

vii) Security and Privacy
Security and privacy are open issues that need to be considered more so for localization systems with remote access in a resource-constrained environment. Most authors used LPWAN technologies for communication, and these contain important security and safety vulnerabilities [175, 176]. These vulnerabilities can be exploited by malicious entities and lead to great damage. Security and privacy become more important as the data being exchanged contains location data for vulnerable elderly people. Therefore, providing a reliable security mechanism based on their limitations is a challenging and open issue task.

viii) Devices not designed for users with no digital literacy
In this review, commercial devices, such as smartphones, were used to position and monitor pedestrians, including elderly and dementia patients with little or no digital literacy. Digital literacy is one of the key barriers to adopting the technologies, but it has not been considered in all the works. Because of that, existing initiatives still need to provide adequate monitoring and localization to rural areas with low-literate users since current designs expect literate users.

3.2.5.2 **Recommendations and research opportunities**

i) TTFF techniques adapted to LPWAN
To improve the TTFF, extended and autonomous ephemeris prediction, and AGPS can be done differently. LPWANs can be used to download assisted data packages necessary for faster position fixes and, therefore, reduced energy consumption. To decrease energy consumption and increase autonomy, the provision of assistance data with a validity of up to multiple weeks, as already offered by several companies, should be exploited. This will minimize the download frequency of data and thus allow LPWANs operating in the unlicensed ISM bands to comply with radio regulations. This solution significantly affects accuracy, so a good trade-off needs to be made.

ii) Transmission of pseudoranges based on snapshot data
A significant part of the energy consumption of a conventional GNSS receiver results from the long time required for decoding the navigation messages disseminated by the satellites. With the recent disclosure of GNSS raw measurements in the mass market GNSS receivers in Android devices [177], new trend techniques mainly oriented to IoT devices could be tested and adapted for pedestrian monitoring. We are suggesting that snapshot techniques could play an important role, as they make it possible to determine position by using only a minuscule interval of a GNSS signal. This highly flexible approach allows for multiple configurations, including outsourcing energy-intensive computations to cloud servers, resulting in cheaper, simpler, and more energy-efficient hardware. Although innovative snapshot techniques have multiple advantages, their real-world adoption is currently only starting

but promising. Also, the transmission of raw snapshots is not possible for proprietary LPWANs such as Sigfox or LoRaWAN, communication networks we highly recommend for the environment being considered in this review [21]. Therefore an alternative configuration like the transmission of pseudoranges based on a snapshot of the signals is recommended instead.

iii) LEO positioning
Satellite technologies are moving towards offering a seamless localization solution. For example, Galileo promises better indoor performance than GPS, but we have yet to see any real-world tests. Currently, ephemeris downloads at a bit rate of 50 bits/s, which is the main reason for the prolonged time to attain a fix in a weak signal environment. By increasing the bit rate of the ephemeris broadcast, we can alleviate this problem. Adopting low-earth orbit (LEO) positioning could enhance indoor performance by relaying data at higher data rates [168].

iv) Galileo signal component
One Galileo satellite has recently been reconfigured to emit a new signal (G1 E5 Quasi Pilot) component optimized to serve low-end receiver devices and Internet of Things (IoT) applications. The initial receiver tests have demonstrated that the signal component has the potential to reduce the signal acquisition time by a factor of three compared to the current GPS L5. This is an exciting development for future researchers as this will significantly improve power efficiency [178].

viii) New hybrid localization techniques using LPWAN
Further research into new hybrid localization architectures that try to better adapt to the characteristics of pedestrian monitoring systems in resource-constrained environments would be advisable. For example, there are proposals that merge GNSS with INS, GNSS with PDR, or GNSS with LoRaWAN, but we did not find any proposal fusing GNSS+INS/PDR+LoRaWAN. The fusion of inertial navigation and GNSS allows for infrastructure-free positioning, and LPWANs such as LoRaWAN provide the possibility for long-range private network deployments by working in a license-free spectrum, its open access

specifications. LoRaWAN also provides energy consumption management using different class-type definitions and adaptive data rates.

Combining the three technologies can also help minimize power consumption by determining when there is a need for the modules to be off and on or their sampling/frequency rate.

3.2.6 Conclusions

We have managed to provide an in-depth, state-of-the-art systematic review of remote pedestrian localization systems with the aim of identifying if they are suitable for resource-constrained environments. We used the PRISMA model as the basis of our literature review in order to provide a replicable work and report the studies' main findings. Although the search queries provided 932 works, only 37 fulfilled all the criteria established in this work and were analyzed, and the key information was extracted to answer the five defined research questions along with the article in various sections.

This systematic review has demonstrated that several general surveys and reviews exist related to localization systems, but none has been done considering a constrained environment, yet these environments exist. From the results of the systematic review, it can be concluded that many of the proposed systems are not suitable for resource-constrained environments, as they assume the availability of resources and infrastructures such as Wi-Fi networks, cellular networks, the Internet, and power grid access.

It has also been noted that the usual features of a remote monitoring system trying to take care of energy consumption usually include a GNSS receiver (mainly GPS) as the main source of location information, LPWAN technologies (mainly LoRaWAN) for data communication, use of inertial sensors mainly to try to reduce GNSS consumption, and custom-made user devices, which allows choosing components and technologies with lower power consumption compared to commercial devices.

However, as discussed in Section 3.2.5, there are opportunities for further work in designing pedestrian monitoring systems that are better suited to these environments. For example, with location acquisition being one of the most important and, at the same time, most consuming components, it is noted that little research has been done on the fusion of GNSS, LoRaWAN, and inertial sensors. Although these technologies are used in many proposed systems, they are used in a loosely coupled manner, and more could be made of their complementarity in terms of consumption and location information.

In conclusion, GNSS is still the best choice for remote, long-range infrastructure-free localization. However, further reduction of the GNSS receiver energy consumption is necessary. Therefore, research should aim to mitigate its challenges rather than eliminate its use in a resource-constrained environment. Therefore, we recommend combining GNSS, INS/PDR, and LoRaWAN, following the suggested co-design and co-creation good practices. Low-cost MEMS sensors, such as accelerometers, gyroscopes, and magnetometers, like GNSS, do not rely on external infrastructure. Combining these technologies can further minimize power consumption by applying different energy-optimization techniques, as will be discussed in chapter 4.

CHAPTER

4

GNSS Power Optimization Strategies

Chapter 3 has provided a comprehensive overview of localization technologies, measuring metrics, and position estimation methods, emphasizing their applicability in resource-constrained environments. It also provides a thorough, up-to-date, systematic review of current outdoor remote pedestrian localization systems, evaluating their suitability for resource-constrained environments. GNSS technology emerges as the preferred choice for long-range localization, albeit requiring further energy efficiency improvements. Power optimization is critical in designing remote localization systems, particularly in remote resource-constrained (harsh) environments where access to electricity and other resources is limited. The devices, often powered by batteries and alternative energy sources, must prioritize long battery life and low energy consumption. Given the limited battery energy, effective power optimization is essential to extend the life of these batteries for several years without the need for frequent charging.

Therefore, this chapter presents the common power-saving strategies and techniques (device battery-saving strategies) used in other studies in section 4.1, and section 4.2 presents the different GNSS power-saving strategies. Finally, Section 4.3 presents the state-of-the-art GNSS activation methods.

4.1 Power consumption in monitoring systems

This subsection will delve into the various optimization strategies, in general, successfully deployed by other authors, underscoring their significance in this context.

4.1.1 Localization techniques

Each technology comes with its unique power challenges, as illustrated in Table 4.1, and understanding these challenges is crucial in selecting the most suitable localization technology. For instance, while offering the best localization solution for outdoor environments, the standard GNSS technology was not originally designed with low energy consumption in mind, leading to high power consumption compared to other technologies [20]. A standard receiver on the IoT market uses 17 mA while acquiring signals and consumes between 0.5 and 8 mA during tracking, with a power supply range of 1.4 to 4.3 V [179]. A GNSS receiver uses more energy during the initial signal acquisition phase than the subsequent tracking mode [20].

As an alternative to GNSS, terrestrial LPWANs, such as NB-IoT and LoRaWAN, are used to estimate the location of a mobile transmitter. Most LPWAN localization systems work through the “localization by communication” concept, i.e., by sending an uplink message. Therefore, the energy consumption of positioning techniques, such as RSS (ranging and fingerprint), TDoA, and AoA, equals the energy consumption of this uplink communication using a specific LPWAN technology. The other advantages of these technologies are the optimized energy consumption profiles for IoT use cases and the ability to provide location updates in outdoor and indoor environments. The biggest challenge of LPWANs is positioning accuracy (order of hundreds or even thousands of meters), as illustrated in Table 4.1, which is rather limited compared to GNSS (not suitable for pedestrian localization), and the coverage is bound to the range of the often nationwide terrestrial networks [20]. For example, the study in [22] about the feasibility of adding a GNSS receiver to a LoRaWAN tracking device in terms of battery lifetime, location accuracy, and location update rate shows that a GNSS receiver should only be omitted if a location error of more than 100 meters is acceptable and the energy budget is extremely constrained.

	LPWAN			LEO			GNSS			
	RSS	T(D)oA	AoA	LEO + LPWAN	Doppler at satellites	Doppler at UE	Snapshot GNSS	GNSS + LEO	A-GNSS	GNSS
Hardware availability	5	5	3	3	4	3	4	3	5	5
Network accessibility	5	5	5	4	3	4	5	4	5	5
Energy consumption profile	5	5	5	3	3	3	3	2	2	1
Localization accuracy	1	2	3	3	3	4	4	5	5	5
Ubiquity of coverage	3	2	3	5	4	4	4	5	4	4
Scalability	5	4	4	5	4	4	4	5	4	5
TTFF	5	5	5	3	2	2	4	2	4	2
Data rate & BW	-	-	-	-	-	-	-	-	-	-
Interoperability	5	5	5	5	5	5	5	5	5	5
Communication of observables	5	5	5	5	5	5	5	5	5	1
Index of technology readiness and maturity	5	5	4	2	3	2	3	4	5	5
Standardized or proprietary	-	-	-	-	-	-	-	-	-	-
UE cost	5	5	5	3	2	4	4	2	3	4
UE complexity	5	5	5	4	4	3	4	3	3	3
Location update rate	4	4	4	3	2	4	4	2	5	5
Local or remote processing	-	-	-	-	-	-	-	-	-	-

Figure 4.1: Compares the performance of LPWAN, LEO, and GNSS technologies across 16 dimensions [20].

INS, a self-contained navigation technique in which measurements provided by gyroscopes and accelerometers can only track the position and orientation of an object or user relative to a known starting point, velocity, and orientation. INS typically provides accurate solutions only for a short duration. Since acceleration is integrated twice to determine position, any error in acceleration measurements accumulates, introducing bias in the estimated velocity and causing continuous drift in the position estimate by the INS [180]. Thus, it works best in combination with other technologies, such as GNSS [171], that provide absolute positioning. This knowledge empowers us to make informed decisions in our research and engineering efforts.

Low Earth Orbit (LEO) is an emerging long-range infrastructure positioning technology brimming with potential. LEO satellites are approximately 20 times closer to Earth than GNSS satellites. Consequently, a LEO satellite signal reaches Earth faster, enabling low-latency communication. In addition, the signal often arrives stronger, enhancing penetration in harsh environments. Finally, LEO satellites provide stronger interference resistance, better spoofing protection, and, similar to LPWAN, the ability to communicate the location of remote devices [20]. The disadvantage is that most existing systems currently focus primarily on communication. Also, the technology is not yet mature and ready for reliable use, as illustrated in Table 4.1.

4.1.2 Communication protocols

Since most efficient localization technologies use cloud computing, and we are examining remote monitoring in this study, it is very important to select a low-power communication network/protocol, as each protocol plays a vital role in battery life due to the difference in power consumption for each protocol [181].

Low-power communication protocols are needed to reduce the energy consumption and overhead of the device's communication using various strategies, such as simple and brief messages, low duty cycles, low data rates, multi-hop routing, and mesh topology, to maximize energy use.

Communication technologies such as cellular and Wi-Fi are high-power consumption networks, as illustrated in Figure 4.2. Notable examples of energy-efficient networks include LoRaWAN, BLE, ZigBee, and 6LoWPAN, which use mesh topologies. Also, energy-efficient communication protocols, such as message queuing telemetry transport (MQTT) [182] or constrained application protocol (CoAP) [183], which have lightweight overhead and support asynchronous communication, can help optimize power consumption. These protocols provide reliable, long-range, and secure communication but have drawbacks such as scalability, latency, and interoperability.

Equally, different authors have come up with different architectures to minimize power consumption. For example, the authors in [62] used a hybrid tree topology to create a layered hierarchical layout with a cluster head that coordinates communication and concatenates the data to be forwarded to the central system via LoRaWAN and, thus, reducing the power consumption. Instead of direct LoRaWAN connectivity as in star topology, utilizing data concatenation at the cluster head drastically reduced the overall energy overhead. Packet concatenation is proposed as an alternative to reduce the energy cost of the packet header and to decrease the overall latency in this study.

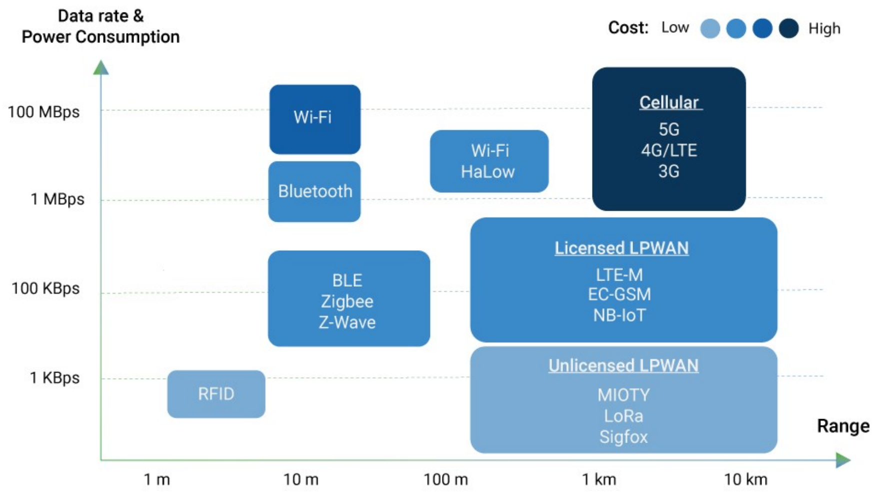


Figure 4.2: The main communication protocols and their impact on power consumption [184].

4.1.3 Devices

One of the most effective strategies for minimizing power consumption is using low-power sensors and nodes. The design of these sensors plays a significant role in determining the amount of power drawn from the devices. This is particularly crucial for battery-powered devices used in building remote localization systems. Opting for low-power devices can significantly extend the battery life, a key advantage in IoT applications.

To ensure your device functions as intended, it's crucial to prioritize power optimization during development. The decisions you make as a developer can play a significant role in making your battery last longer. For example, selecting an energy-efficient Microcontroller Unit (MCU), minimizing the number of internal peripherals, and turning off unused peripherals are good practices for reducing power consumption. Choosing components with low power requirements (low-noise amplifiers, oscillators, real-time clocks) results in improvements in power consumption that add up during the operation of the GNSS receiver [74]. End devices such as Sigfox, LoRa, and NB-IoT are in sleep mode most of the time outside operation, thus maximizing battery life. The flexibility of choosing what to use makes custom-made devices more power-efficient than commercial ones.

Another effective strategy for minimizing device power consumption is adaptive voltage scaling (AVS). AVS is a more advanced power management technique for IoT devices, which dynamically adjusts the supply voltage of the device's components according to their performance and workload requirements. This is done by optimizing the device's power efficiency by reducing the voltage when the device performs low-intensity tasks or is idle and increasing the voltage when the device needs to perform high-intensity tasks or meet deadlines [185]. Unlike other methods, AVS is a closed-loop control system that handles process variation between devices and shifts in digital load, temperature, and process aging that affect the device's characteristics and behavior. However, this technique requires a sophisticated control algorithm and a feedback mechanism to regulate and monitor the voltage.

4.2 GNSS power optimization strategies for resource-constrained environments

Although GNSS offers highly accurate and widely available position and time information, as already explained in chapter 3, the technology's power consumption is challenging for a resource-constrained environment and more so for battery-powered IoT devices that must operate for months without charging. This is why many Internet of Things (IoT) applications, which value battery life more than location accuracy, benefit from options like localization via Low Power Wide Area Networks (LPWANs) such as LoRaWAN [23, 24, 25]. However, this results in large estimation positioning errors [22], which means that, as indicated by the systematic literature review conducted by authors in [26] about state-of-the-art remote pedestrian monitoring systems for resource-constrained environments, GNSS technology is still the best choice for accurate and reliable remote localization of pedestrians. Therefore, research should aim to lessen GNSS' challenges rather than eliminate its use in resource-constrained environments. Several techniques to overcome this inconsistency are proposed in the white paper about power-efficient positioning for the Internet of Things by the European GNSS Agency (GSA) [21]. The following discusses these strategies for GNSS power optimization as illustrated in Figure 4.3. We also discuss their suitability in relation to resource-constrained environments.

4.2.1 Assisted-GNSS

According to the GNSS Technology Report 2020, a typical receiver in the IoT market consumes $17mA$ during signal acquisition and 0.5–$8mA$ during tracking, using a power supply of 1.4–4.3V [186]. A GNSS receiver consumes more energy during the initial signal acquisition than during the subsequent tracking mode. Hence, the TTFF has a significant impact on overall energy consumption. TTFF is the time a GNSS receiver needs to produce a valid coordinate within a certain performance (e.g., in terms of accuracy). The TTFF depends on the start mode the GNSS module has to perform when it is switched on. A GNSS module has four different starts: cold, warm, assisted, and hot [187].

Therefore, several energy-saving GNSS techniques are focusing on TTFF reduction. During a cold start, all possible frequency and code delays are searched, and the ephemeris and broadcast time are decoded, i.e., no information is available at the receiver, and therefore, the receiver entails a full search of the sky for all satellites. In a warm start, only the broadcast time and ephemeris need to be decoded, as the frequency and code delays are already known. In a hot start, all necessary data—frequency and code delays, broadcast time, and ephemeris—are already known. Modern GNSS modules feature assisted positioning, which allows for the downloading of ephemeris and broadcast time information to achieve a quicker TTFF [187].

The widely adopted GNSS techniques, such as extended and autonomous ephemeris prediction [30, 188] and AGPS [28, 29, 179] as illustrated in Figure 4.3, ensure all data needed to compute a location is present, successfully omitting power-hungry satellite communication to retrieve, e.g., coarse location, almanac, the satellite status, time, or ephemeris data, dramatically improving the TTFF (the shorter the acquisition phase, the less power the GNSS receiver consumes) [77]. Another benefit is higher receiver sensitivity, which improves performance in difficult environments, such as urban and indoor [21]. However, all these techniques require a stable communication channel to access the Internet with sufficient capacity and data rates, which are unavailable in resource-constrained environments, complicating the applications of these strategies in resource-constrained environments.

4.2.2 Cloud-based GNSS computing

While assisted GNSS implementations (A1, A2, and A3), as illustrated in Figure 4.3 already reduce energy consumption, downloading assisted data from an external network isn't always feasible, and some applications demand even stricter energy efficiency that these techniques can not fully address. A paradigm shift in position calculation is necessary to achieve significant energy savings. Instead of having a single receiver handle all GNSS tasks, energy-intensive functions like position determination from retrieved pseudoranges can be offloaded to the cloud, where sufficient energy, processing power, and clock and ephemeris data are available in virtually unlimited quantity.

The white paper by [21] identifies P1 (transmission of pseudoranges), P2 (transmission of pseudoranges with support data), S1 (transmission of raw snapshots), S2 (transmission of pseudoranges) solutions as best suited for cloud processing as illustrated in Figure 4.3. A significant portion of the energy consumption in a conventional GNSS receiver is due to the lengthy process of decoding satellite navigation messages. One way to eliminate this time- and energy-intensive step is by transmitting pseudoranges to an external computing facility (cloud) for position determination. To streamline this process and further reduce battery consumption, the acquisition search space can be limited by supplying the receiver with support data, such as the Doppler range of visible satellites, a technique known as acquisition assistance. The big challenge of this method is that only a few start-ups currently offer cloud-based positioning based on transmitted pseudoranges for IoT applications.

Unlike the other GNSS techniques, snapshot techniques (S1 and S2) are unique in that they allow the determination of position using only a minuscule interval of a GNSS signal. Snapshot processing techniques as used in [16, 33, 34] and [100] constitute the most recent set of energy-saving GNSS techniques. This highly flexible approach allows for multiple configurations, including outsourcing energy-intensive computations to cloud servers, resulting in simpler, cheaper, and more energy-efficient hardware. The main idea of these cloud processing techniques is to sample only a short portion (about 20 ms) of the received satellite signal (referred to as a snapshot), digitize the samples, and transmit them via a connectivity link to the cloud, where the data is processed with the help of assistance data to retrieve pseudo-range information, and the pedestrian location is calculated. For example, a baseband technologies' snapshot receiver lasts 18 days to 1 year, depending on the snapshot length, while a conventional receiver would only last 2 hours on the same 10-mAh battery [20].

When implementing snapshot-based position determination, several configurations(S1 and S2) are feasible depending on multiple factors, with the up-and downlink capacities of the network being the most important, as illustrated in Figure 4.3. The transmission of raw snapshots (S1) is the most well-known configuration. This method sends the digital sample directly to the cloud, where all post-processing and position determination are carried out. However, this configuration can only be feasible with networks that provide sufficient data uplink capacity [21]. An alternative configuration, like the transmission of pseudoranges based on a snapshot of the signals, must be used instead, as under this, the signal processing partly remains on the device, resulting in a significantly reduced amount of data that needs to be exchanged with the cloud, i.e., the uplink to the remote server comprises mainly a set of pseudoranges of just a few bytes.

Although innovative snapshot techniques have multiple advantages, their real-world adoption is still limited but promising. The techniques require the GNSS signals to be captured with a specific minimum resolution, which demands complex receiver hardware capable of capturing multi-bit data at sampling rates of 16 MHz and more [189]. It also requires an internet connection, a resource very limited or unavailable in constrained environments. Several interests exist in cases where the GNSS receiver is connected to an LPWAN transceiver, and the latter is used to transmit snapshot data to a processing center for subsequent outsourced position calculation. The transmission of raw snapshots is not possible for proprietary LPWANs such as Sigfox or LoRaWAN because of their limited payload length of a single message [21], as illustrated in Figure 4.3.

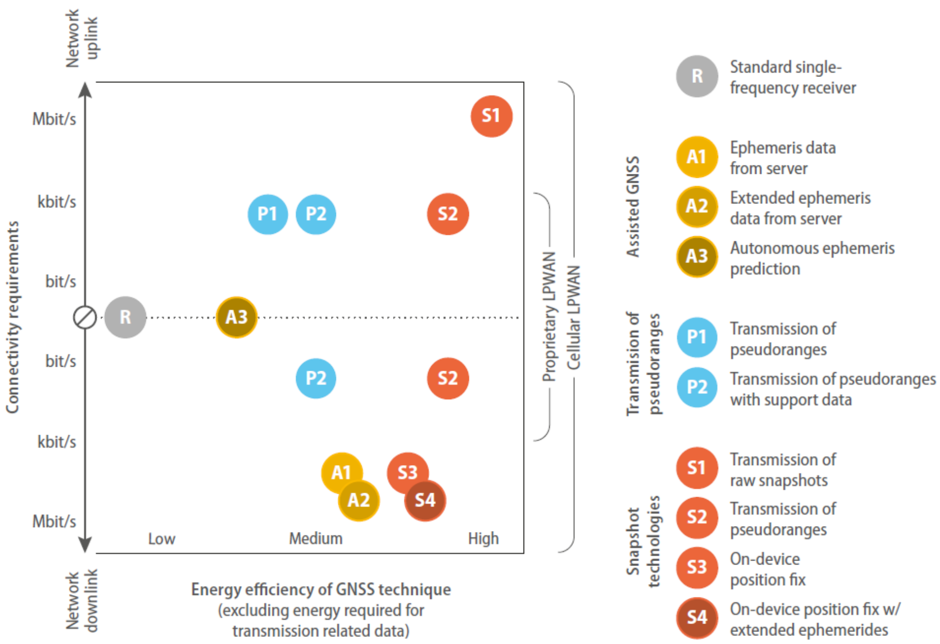


Figure 4.3: Relationship between connectivity requirements and energy efficiency of different GNSS techniques [21].

4.2.3 **Duty cycling/sleep modes**

Recognizing that positions are often required on demand rather than continuously, duty cycling consists of powering off all the components of a receiver except those needed to react to a wake-up call, thus drastically reducing its power consumption. This technique is currently implemented in virtually all mass-market GNSS receivers.

Utilizing these sleep modes (deep and light) is one of the most effective ways to save power in IoT devices. Light sleep mode consumes moderate power, allows for short wake-up times, and partially preserves the device's state by keeping some RAM and peripherals powered, making it suitable for applications requiring frequent wake-ups and quick response times. In contrast, deep sleep mode minimizes power consumption to the lowest level, entails longer wake-up times, and preserves minimal state information, as most components are powered down, making it ideal for scenarios where maximum power savings are crucial and wake-ups are infrequent. A smart sensor could enter a sleep mode that powers down its measurement systems when it is not actively taking readings. For example, consider a wildlife tracking sensor used to monitor animals in a remote forest. These sensors can spend most of their time in a deep sleep mode, waking up only to record and transmit location data at predefined intervals. This technique significantly extends the life of their batteries, sometimes allowing them to operate for months or even years without a battery change.

Devices can be turned off or go to sleep mode when there is no signal, indoors, or when other technologies are being used. For example, authors in [70, 151, 161, 171] and [157] turned off GPS when there was no signal and when indoors to decrease power consumption. This technique may not work efficiently in most remote areas as housing infrastructure in these resource-constrained areas can still allow access to GNSS signals indoors.

The duty cycling approach requires careful consideration of the specific use case and the criticality of the solution. For continuous data acquisition applications, balancing power efficiency with functionality is essential. Conversely, deeper sleep modes can significantly extend battery life for non-critical applications or those with infrequent data transmission, especially in IoT use cases where a location update is only required every few hours, days, weeks, or even months. However, when a GNSS receiver has been powered off for a while (more than two hours), it must typically perform a cold start to obtain and decode information from at least four satellites in view. This requires a substantial amount of energy; therefore, a good trade-off should be made to minimize the overall power consumption [22]. Also, the energy consumption profiles of technologies, such as LPWAN, show a peak in current consumption during message transmission and in the idle period, highlighting the need for sleep modes [20].

Also, power interruptions cause GNSS receivers to lose their position fix and all downloaded time and GNSS orbit data, forcing them to undergo a complete cold start when power is returned. By saving this data in backup RAM, GNSS receivers with a backup battery can recover more quickly from interruptions in the power supply, thereby saving power. When the position update period is longer than two hours, which corresponds roughly to the validity of the ephemeris data, the backup battery becomes unnecessary and can be left out, reducing power demand [74]. Integrating a real-time clock allows the GNSS receiver to start up more quickly when the main power source returns, reducing power consumption during power outages. However, as the real-time clock requires a battery as a backup power source, it increases the size of the solution and adds cost.

4.2.4 Multi-constellation and multi-frequency receivers

A larger number of satellites in view results in improved position accuracy and higher signal availability, particularly in urban environments where buildings might partially obscure the line of sight to the satellites. Thus, multi-constellation receivers are always advisable, so satellites from all the available systems, i.e., Galileo, GPS, GLONASS, and BeiDou- are leveraged [21]. The number of concurrently tracked GNSS constellations significantly impacts power consumption, mainly when the constellations transmit in different frequency bands. It also comes at a cost, as tracking more GNSS constellations increases position availability, especially when sky view is limited or small antennas are used. In such challenging environments, receiving signals from multiple bands (L1, L2, L5) can increase the positioning accuracy by mitigating multipath effects. On the other hand, regionally constrained installations can save power without impacting performance by carefully selecting which constellations to track based on their geographic location. When high-position accuracy and short acquisition times are of the essence, GNSS receivers need to download satellite ephemeris data every 30 minutes for tracked satellites. The more constellations the receiver tracks, the more often this happens. Because the GNSS receiver needs to be switched on to download ephemeris data, this is only possible in continuous tracking mode, where the receiver cannot save power [74]. Reducing the number of tracking channels and tracking a minimum number of satellites required to estimate position, the receiver can proportionally save power [190].

4.2.5 Update rate

The update rate, which can be defined as the frequency with which the positions are calculated on the device or at an external processing facility or the time interval between two position calculations, should be the first thing to consider when seeking to reduce a receiver's power consumption. This is because GNSS receivers' power consumption is essentially related to user requirements. While some use cases require continuous tracking, others require up to one position reading per minute, hour, or day. This rate significantly impacts the battery life, with high update rates leading to more on-time for the devices and, hence, high energy consumption. For example, most GNSS receivers in continuous tracking mode support 10 Hz or even higher update rates [74]. However, some everyday use cases, like tracking pedestrians or elderly people around homes like in our user case, only require position updates on request or at the event. So, by reducing the update rate to meet a use case's actual requirements and allowing it to enter power save mode between updates, the GNSS receiver can dramatically reduce its power demand.

In this study, we categorize the update rate as periodic [24, 169], on request [76] when the update is triggered by the user or by a remote device, and on the event, [16, 76, 152, 153, 170, 171] when the measurement update is initiated by the local device when a specific event occurs, e.g., when a temperature sensor exceeds a critical threshold.

For example, most GNSS receivers in continuous tracking mode support 10 Hz or even higher update rates. However, some everyday use cases, like tracking pedestrians or elderly people around homes, only require position updates on request or at the event. So, by reducing the update rate to meet a use case's actual requirements and allowing it to enter power save mode between updates, the GNSS receiver can dramatically reduce its power demand. This can easily be achieved by hybridizing GNSS technology with other infrastructure-free technologies, like inertial navigation systems.

4.2.6 Hybridization of technologies

Hybridization, as discussed more in section 3.1.2.3, involves the combination of two or more localization technologies. The hybrid method takes advantage of the strengths of one system and combines it with another system with strengths where the first system exhibits inhibitions to compensate for the limitations of single model positioning technologies [86]. For example, authors in [22, 71, 99, 100, 153, 157, 165, 171] combined GNSS, a global technology, with other technologies such as Wi-Fi, INS, and BLE to minimize the relatively high energy consumption in its typical use case. This is done by turning off GNSS receivers when they are not in use or in places without satellite signal access. For example, the authors in [153] enhanced the battery life by 50% compared to GNSS alone by combining GNSS+Wi-Fi+INS.

4.2.7 Brief conclusion

In conclusion, today's state-of-the-art GNSS receivers typically offer numerous means of optimizing their power consumption while meeting use case-specific performance requirements, as discussed above. Precisely which design considerations and device configurations apply to a specific use case will depend on carefully balancing these four competing factors as illustrated in Figure 4.4. This is because these four factors (size, cost, performance, and power) are intimately connected, so any measures to reduce power consumption will impact a product's performance. Effectively balancing these characteristics to suit a specific application or use case demands a thorough understanding of the technology, hardware, software, and services involved. These factors are largely dictated by the use case they are addressing.

Although tremendous progress has been made in enhancing the power efficiency of GNSS technology, further research remains crucial in optimizing energy consumption for battery-operated devices designed for challenging environments. This is mainly due to the reliance of these power optimization strategies/systems on resources and infrastructures, such as cellular networks, Wi-Fi networks, the Internet, and access to the power grid, as well as resources limited or not available in these environments. Therefore, without these resources, techniques such as snapshots, cloud computing, and AGPS will not work effectively in a constrained environment.

With the use case at hand, it is imperative to focus on GNSS activation strategies and methods, such as location update rate and sampling rate, that can be applied in these environments without incurring additional costs for the infrastructure needed for most strategies to operate.

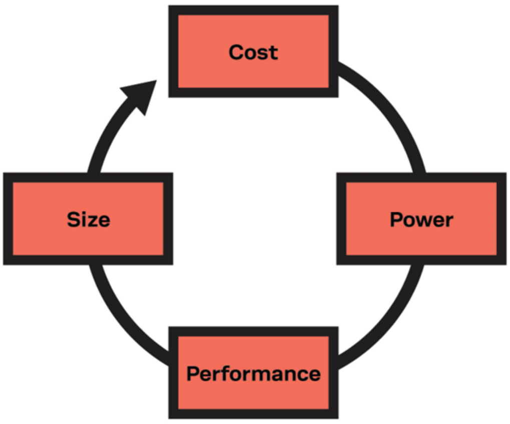


Figure 4.4: The four competing factors are intimately connected and greatly impact any measures to reduce power consumption [74].

4.3 GNSS activation methods: State of the art

Energy efficiency is a critical concern in remote pedestrian localization systems for resource-constrained settings. A significant portion of energy is consumed by the GNSS module in continuous positioning [27]. GNSS activation refers to strategies for varying the position update rate or turning the receiver on and off intelligently to conserve power. Recognizing that positions are often required on demand (when an event is triggered) rather than continuously, reducing the update rate to meet a use case's actual requirements and allowing the GNSS receiver to enter power save mode (turned off when not in use between updates) can dramatically reduce its power demand [74]. Therefore, this section will concentrate on GNSS activation techniques aimed at optimizing power consumption based on our user case.

As explained in section 4.2.5, there are some use cases where a location update is only required every few hours, days, weeks, or months, or even in instances where an event is triggered. Our focus in this study is on monitoring elderly people around their homes living in remote resource-constrained environments, and this does not call for continuous tracking. With this in mind, the question is when to activate the GNSS receiver to take the position reading. Different studies have used several methods and techniques to activate the GNSS. These methods can be categorized as user position-based and activity-based, although many studies combined both. Recent research has sought more intelligent, often machine-learning (ML)-assisted, methods that overcome the limitations of these basic strategies. Next, we will review some of these works about different GNSS activation methods and discuss their suitability for resource-constrained environments.

4.3.1 Position-based methods

The position-based method uses the user position to eliminate unnecessary GNSS activations and/or position updates. Beacons such as Infrared and Bluetooth devices are commonly installed at the user's premises to determine the user's position around their premises, usually by proximity. For example, authors in [165] used Bluetooth beacons, GNSS signal strength, and an accelerometer to detect static periods, determine if the user is indoors, and then turn off the GNSS. It should be noted that installing beacons is not ideal for most resource-constrained environments because of the costs (additional infrastructure) involved and the nature of the housing infrastructure found in these environments, as illustrated in Figure 4.5. Works effectively well in planned, structured homes, commonly in urban centers. Plus, GNSS receivers can continue getting a good signal even when the user is indoors because of the nature and materials used to set up those houses.

Authors in [171] designed an energy-efficient location tracking service, SensTrack, which provides the user's moving trajectory while reducing its impact on the device's battery life. SensTrack smartly selects the location sensing methods between Wi-Fi and GPS and reduces the sampling rate and the time the GPS receiver needs to be activated by utilizing the information from the acceleration and orientation sensors, two of the most common smartphone sensors today. This is done by turning off the GPS when there is no signal and when indoors, and Wi-Fi is then used for localization, also reducing the sampling rate. Like in [165], signal strength may not be an excellent method to determine whether the user is indoors, more so in resource-constrained environments.

Several other works have explored machine learning (ML) techniques to determine if the user position is indoor or outdoor. Authors in [191] used a clustering technique known as Inductive System Monitoring (ISM) to build a GNSS component activation mode by detecting indoor/outdoor scenarios using LTE cellular signal strength. Authors in [192] leveraged GNSS measurements from Android smartphones to detect indoor/outdoor complex environments. Supervised ML algorithms are then used to predict indoor/outdoor status, which is interpreted as the observations of the Hidden Markov Model to detect the user transition between indoor/outdoor in complex scenarios. It is important to note that in their work, they just detect indoor or outdoor but do not activate/deactivate GNSS since they need the GNSS signals to make such classification. However, it should be noted that there is limited or no access to cellular networks in most resource-constrained areas, and also, because of the nature of the housing infrastructure in this area, signal strength outdoors and indoors could be very similar, and thus, their methods may not work effectively.

4.3.2 Activity-based methods

Under activity-based, user activity parameters, such as acceleration or angular rate and velocity have been used by different authors [99, 165, 193, 194, 195, 196] to control the position update rates and GNSS activation.

For example, authors in [197] propose a rate-adaptive positioning system (RAPS) designed to optimize GPS usage in urban environments. RAPS reduces GPS power consumption by activating it only when needed, based on user location history and velocity estimates. It incorporates a duty-cycled accelerometer for movement estimation and Bluetooth for sharing location data among nearby devices to minimize uncertainty. Additionally, RAPS uses cell tower RSS blacklisting to avoid GPS activation in areas where GPS signals are likely unavailable, such as indoors. This proposal is designed for urban environments, where GNSS is generally less accurate, so it suffices to turn on GNSS only as often as necessary to achieve this accuracy. In addition, building a location-time database makes the user device more complex and with higher communication requirements.

Similarly, authors in [196] developed an accelerometer-based algorithm for correctly detecting the user's mobility state. The novel algorithm was designed, built, and tested on Android-powered mobile devices. It was used to control the process of turning on and off smartphone-based location-sensing technologies like GPS. Like in [197], just acceleration determines when to turn on/off the GPS, and it is not effective, especially with pedestrians.

In [193], the authors adopted and implemented a method known as the accelerometer-assisted GPS Model, originally developed by the authors in [196]. This method employed the built-in 3-axis accelerometer to determine whether the user was stationary. To modify the GPS receiver's sampling rate and minimize power consumption, the authors focused on two motion patterns: stationary and movement. When a pedestrian was stationary, the system would suspend GPS sampling for positioning. Conversely, when the pedestrian began to move, the system adjusted the GPS sampling rate based on the correlations between the maximum search range, the service area, and the individual's current location. Their approach considered the individual's position rather than solely the mobility state. The location of a user was assessed in relation to points of interest, such as heritage sites, scenic areas, landmarks, popular shops, or nearby restaurants. To gather this contextual information, pedestrians continuously updated their geographical locations via the cellular network, regardless of whether they were in motion or at rest. Although the authors incorporated the concepts of a geofence and user position, the system's design is not suitable for resource-constrained environments as it relies on network connectivity and reference points, such as popular stores or restaurants, to ascertain the user's location—resources that are typically unavailable in rural, resource-limited settings.

Based on our analysis, existing activity-based GNSS activation methods can be broadly classified into three categories:

- Acceleration thresholding methods, which rely on a predefined acceleration threshold to activate GNSS. These methods are simple and straightforward but result in frequent unnecessary activations for typical home-based movements, thus saving minimal energy in our scenario.

- Walking detector methods, which trigger GNSS upon detecting general walking. Current literature typically focuses on generic walking detection without distinguishing the context or specific types of walking (e.g., walking at home vs. walking away from home). Typical characteristics examined in these methods include the number of steps per second, walking pace/speed, heading stability, and overall movement intensity.
- Multiple modes of transport classifiers, designed to differentiate various transportation modes such as walking, cycling, and driving. Although effective in multi-modal contexts, these methods are excessively complex for our resource-constrained scenario, where walking is the predominant, if not exclusive, mode of transport.

In contrast to these approaches, we hypothesize that explicitly detecting the activity of ”walking away” rather than general walking is possible and sufficient for our use case. This specificity can significantly improve energy efficiency by reducing unnecessary GNSS activations, particularly suited to rural, resource-constrained environments. Importantly, our objective is not to pinpoint precisely the exact second a person leaves home but to maximize energy savings through timely and contextually relevant GNSS activations, leading to meaningful battery-life improvements measured in hours rather than seconds. It should be noted that this is an improvement and contextual adaptation rather than a complete paradigm shift.

In summary, the activity-based method may work on objects that are either static or changing their position, such as cars, but may not be an optimal solution to optimize power in the case of human users as subjects like in our case because, by nature, human beings exhibit frequent motions that can be easily captured and interpreted as an activity to trigger the turn-on of the GNSS, yet it is a false alarm.

4.3.3 ML-based Human Activity Recognition methods

Human Activity Recognition (HAR) involves the application of ML algorithms to sensor data from devices such as smartphones and wearables to identify and classify human activities, including walking, running, bathing, and cooking [198]. These classifications (activities) can be leveraged to estimate the user’s position around the homes (domestic environments) and optimize GNSS activations, a critical consideration in resource-constrained settings. HAR is a very active research topic in the field of sensing, pervasive computing, and localization, with many applications in real-world scenarios such as smart environments, health and well-being, surveillance and security, human-computer interaction, etc. [199].

HAR systems typically rely on inertial sensors such as accelerometers, gyroscopes, and magnetometers to capture low-level activity patterns. For example, accelerometer sensors measure dynamic (e.g., vibration or movement) and static (e.g., gravity) forces of acceleration acting on the sensor, providing valuable data in detecting user movement patterns such as walking speed and step length. The gyroscope sensor measures the angular velocity, i.e., the rate of change of the sensor's orientation, providing information for detecting patterns in user activities that involve rotation around a particular axis. Combining these two inertial (accelerometer and gyroscope) sensors provides a more reliable mechanism to distinguish numerous human activities [199].

Model selection is a crucial aspect of Human Activity Recognition (HAR), as it determines the ML algorithm or model used to classify and predict human activities based on the collected sensor data. The choice of model can significantly impact the accuracy and performance of the HAR system. Several studies have recommended using diverse classification models for HAR to leverage their complementary strengths. For example, authors in [200] and [201] recommend the use of Long Short-Term Memory (LSTM) networks for activity classification because their recurrent architecture effectively captures long-term temporal dependencies in sequential sensor data, which is critical for discerning subtle temporal variations in human motion. These properties are particularly valuable when the objective is to distinguish between nuanced activities, such as differentiating "walking at home" from "walking away from home."

Similarly, ensemble methods have gained traction in recent works. For example, authors in [202] and [203] advocate using ensemble approaches such as XGBoost for activity classification because these methods can model complex non-linear relationships through gradient boosting. This iterative error-correction mechanism enhances classification accuracy and offers computational efficiency—an essential consideration for deployment on resource-constrained devices. In these studies, XGBoost is praised for its scalability and ability to work effectively with reduced feature sets, as highlighted by using techniques like SHAP for feature selection.

Traditional models such as Support Vector Machine (SVM) and Random Forest (RF) are also recommended in the literature. According to [200] and [203], SVM is favored for generating robust decision boundaries in high-dimensional feature spaces, making it a reliable baseline for many HAR tasks. Concurrently, RF is valued for its classification performance and its inherent ability to provide feature importance metrics, which aid in feature reduction and model interpretability.

Thus, integrating Random Forest, SVM, XGBoost, and LSTM draws on a spectrum of methodologies that address the challenges of activity classification in low-resource environments while ensuring high accuracy and efficiency in GNSS power optimization.

Feature selection is equally critical. The feature selection process in this work was driven by the need to accurately capture the nuances of human motion while minimizing computational overhead-an essential requirement for resource-constrained environments. A range of time domain features (including mean, standard deviation, root mean square, and kurtosis) and frequency domain features (including entropy, energy, and skewness) were extracted from the data. HAR studies have widely validated these features for their ability to characterize the dynamic and static properties of inertial sensor signals [199, 200]. To further refine the feature set, we employed SHAP analysis, which allowed us to quantify the contribution of each feature to the model's predictions. This enabled us to identify and retain only the top ten most discriminative features. The resulting reduced feature set helps prevent overfitting by eliminating redundant or less informative data and decreases memory and processing requirements—critical factors for ensuring efficient operation on low-resource devices [204, 205].

Several authors have explored these human activities to determine when to activate the GNSS. For example, the authors in [206] proposed an approach to accurately detect the indoor/outdoor environment according to six different daily activities of users, including walking, skipping, jogging, staying, and climbing stairs up and down. Even though classifying the user position as indoor or outdoor might result in better results than just using acceleration, knowing the user is outdoors is not enough information, more so in our user case, as being outdoors does not necessarily

Figure 4.5: Traditional house in rural Uganda.

mean the user is lost and needs the caretaker's attention. Plus, most users in rural, low-resourced environments spend most of their time outdoors [35]. This will still cause unnecessary GNSS activation. Notably, no existing HAR method specifically detects a "walking away from home" activity class, nor has any previous work proposed a GNSS activation method tailored explicitly for resource-constrained environments based on detecting this specific class.

Overall, the thesis uses these four models to cover a broad spectrum of ML techniques—from traditional ensemble methods (RF) and kernel-based classifiers (SVM) to advanced ensemble boosting (XGBoost) and deep learning architectures (LSTM). This comprehensive evaluation helps identify a model that not only delivers high classification performance but also meets the computational constraints of our embedded system, with XGBoost emerging as the most balanced choice for deployment.

4.4 Brief conclusion

In this chapter, we have presented the common power-saving strategies and techniques used in other studies. We have also discussed the different GNSS power-saving strategies with an interest in identifying their applicability in constrained environments and presented the state-of-the-art GNSS activation methods, one of the main GNSS power optimization strategies. Three methods have been assessed: activity-based, position-based, and ML-based Human Activity Recognition. Position-based approaches, often reliant on infrastructure like beacons or cellular networks, prove impractical due to cost and limited availability in such contexts. Activity-based methods, while simpler, trigger frequent unnecessary GNSS activations due to their reliance on generic motion detection, lacking the specificity required for our use case. Existing ML-based HAR techniques, although promising, fail to capture the critical “walking away from home” activity needed for our specific use case in rural environments, where being outdoors is common but does not always necessitate GNSS activation. By the nature of the resource-constrained environment use case, the study sought a method smarter than just checking the acceleration or indoor/outdoor user positions and cheaper than using beacons for GNSS activation to fill this gap. This analysis sets the stage for our proposed solution, which employs a carefully selected ML technique that meets both performance and resource constraints in low-resource environments.

CHAPTER

5

Positioning-based GNSS activation

5.1 Introduction

This chapter presents a GNSS activation method that is smarter than checking user acceleration but cheaper than installing beacons for GNSS activation. It proposes a position-based method using the PDR system. Two different PDR systems, pitch-based and acceleration-based, were implemented and evaluated to assess the effectiveness of the proposed method. This method does not need to install beacons at the user premises, making it the best fit for a resource-constrained environment, especially in poor rural areas in Africa with poor housing infrastructure.

The proposed method is based on defining a geofence around the user's home so that the GNSS is only turned on when the user's position is estimated to be outside the geofence (safe zone). Our experiments were conducted in an open environment with limited interference to simulate the low-resource rural home scenario. LoRaWAN technology was used for ultra-low power requirements and long-range bidirectional communication of up to 15km or more in rural areas under Line-of-sight circumstances. The rest of this chapter is organized as follows. Section 5.2 describes the proposed methodology. Details about the experiments and the results are presented in Section 5.3. Finally, this work is summarized and concluded in Section 5.4.

5.2 Methodology

5.2.1 Pedestrian monitoring system overview

The proposed GNSS activation method will be included in a pedestrian monitoring system. This section describes the main blocks of that system as shown in Figure 5.1. Our proposed system has four blocks, i.e., power, sensor, control, and communication modules. The sensor module contains the positioning sensor (GNSS) and inertial sensors (accelerometer and gyroscope). The communication module has a RAK11720 LoRaWAN, and the control module has an ESP32 microcontroller. A lithium-ion battery was used to power all the modules.

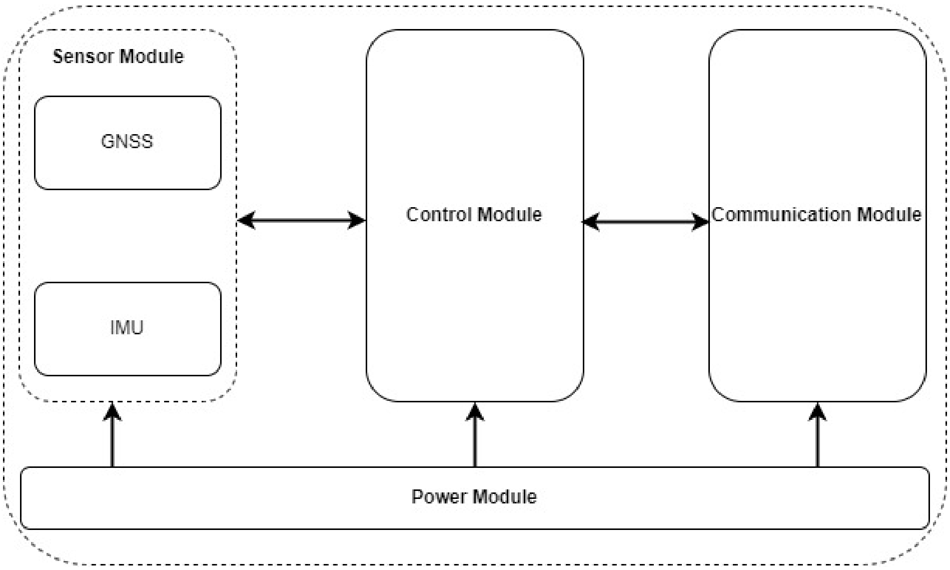


Figure 5.1: Proposed system block diagram.

5.2.2 The proposed position-based GNSS activation method

Figure 5.2 is the workflow diagram of the proposed system. To easily monitor elderly people around their homes, a geofence equivalent to a safe area is defined first. We assumed the user's home was at the center of the geofence (safe zone). When the user turns on the system, the inertial sensors and the GNSS receiver are turned on and then off immediately after a reference point (reading of the coordinates for the initial user position) is acquired and stored permanently. The user is then requested to define the radius of the geofence (safe zone), and it is also stored permanently. We used the geofence idea to define the safe area around the user's home where less or no monitoring is needed. In our environment, we assumed the user could still get a GNSS signal even if indoors. In this experiment, a safe zone with a radius of 20 meters was assumed around the user's home.

In real-time, the user position is continuously monitored and estimated using a PDR system and checked to see if it is in the safe zone. When the user position is estimated to be outside the safe zone radius, the GNSS receiver is turned on, and the reading is taken and compared with the initial position.

If the position is found to be within the safe zone, the GNSS is turned off, the user position on the PDR system is updated and marked as a false alarm, and inertial tracking resumes. In effect, the GNSS is used only to get absolute fixes when needed (exit/entry events or periodic checks), whereas the low-power IMU handles all interim movement tracking. This selective activation significantly reduces power consumption while still guaranteeing that the system knows whenever the user leaves home. However, if the position is confirmed to be outside the safe zone, a message is sent through the LoRaWAN communication system to the caretaker for a quick response.

When the user is outside the safe zone and continues walking, the GNSS receiver's sampling rate is set to 1 minute. This design ensures that once the user is beyond their safe vicinity, the remote monitoring system has up-to-date location data despite the higher power cost, as the situation potentially represents a higher-risk scenario. Further power optimization is applied if the user stops moving (stationary) while outside the geofence. For example, if the user sits or stands still after walking out, our system will turn off the GNSS until motion resumes (similar to the baseline idea, but only applicable outside the safe zone). We implemented this by monitoring the step detection in the PDR: if no step is detected for a short interval (several seconds) while outside, the GNSS is put to sleep. It is reactivated immediately when movement (such as steps) recommences. This ensures that if the user is resting (or perhaps enters a nearby building), the GNSS does not remain on unnecessarily when the location is not changing. Experiment 3 below explicitly tests this scenario.

In that case, the user returns to the geofence as the PDR system estimates; the GNSS is turned off until the user's position is estimated to be outside the geofence or after 30 minutes. We recognize that PDR errors will accumulate over time; therefore, to bound the drift error and maintain satellite data currency, we schedule periodic GNSS fixes every 30 minutes of continued stay within the safe zone. We also used the 30-minute position update rate inside the safe zone for our work to prevent the GNSS receiver from going to the cold start. In other words, if the user has not left home for an extended period, the system briefly activates GNSS twice an hour to calibrate the PDR (correct any accumulated position error) and to download fresh ephemeris data, thus avoiding a cold start if/when a fix is later needed. (This interval was shortened to 5 minutes for practicality during experiments, as explained below.) Power outages cause GNSS receivers to lose their position fix and all downloaded time and GNSS orbit data (ephemeris data), forcing them to undergo a complete cold start (up to 12.5 min) as soon as power is returned. Many GNSS receivers include a backup battery and a built-in EEPROM to boast the Time To First Fix (TTFF) [77]. So, by saving this data in backup RAM, GNSS receivers with a backup battery can recover faster (in less than 30 seconds). This only works when the position update period is not longer than two hours, which roughly corresponds to the validity of the ephemeris data [207]. Therefore, the proposed method assumes that the GNSS receiver includes a backup battery and memory.

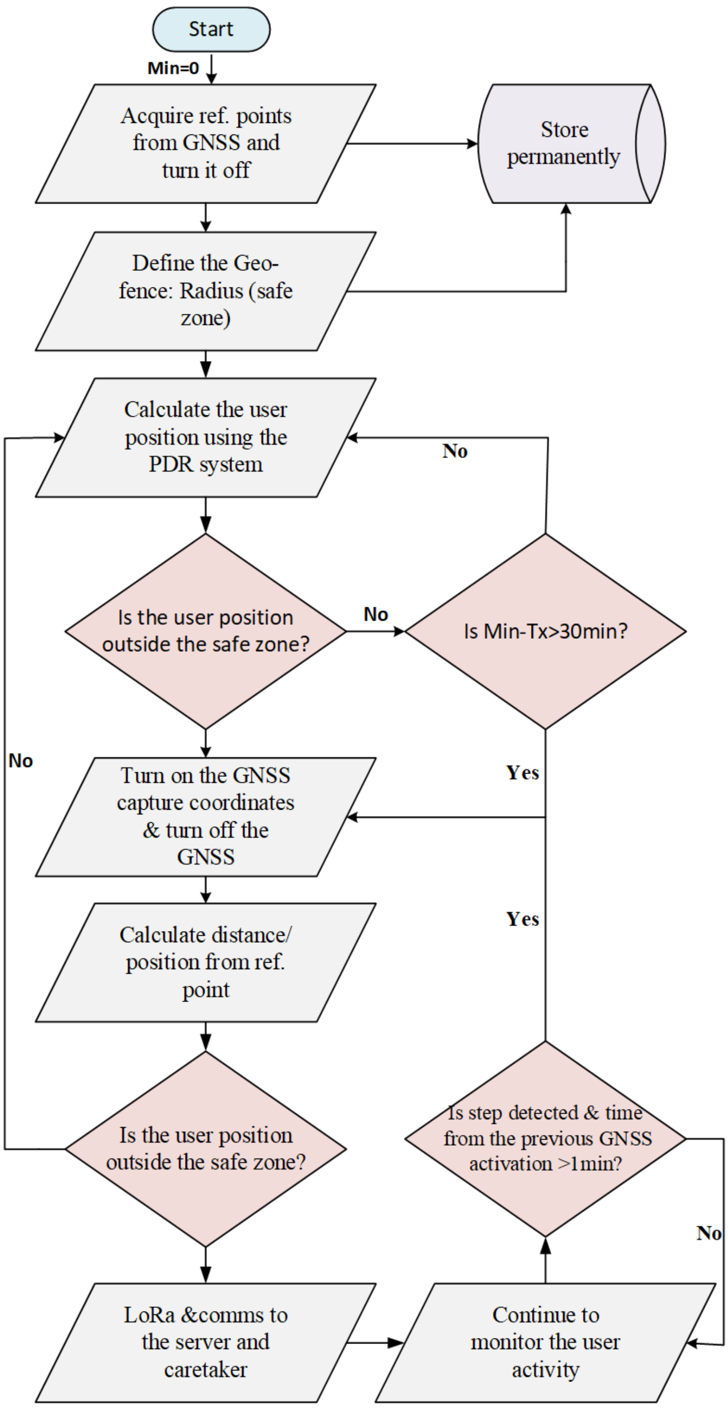


Figure 5.2: Workflow diagram of the proposed system.

5.2.3 PDR system

The proposed GNSS activation and position update rate depend on the user position estimated by the PDR system. So, the accuracy with which the PDR system determines the position is key to the effectiveness of the proposed method. Two different PDR systems were implemented and evaluated to assess this. PDR systems are generally divided into four different blocks: step detection, step length estimation, heading estimation, and, finally, position integration. The two implementations differ only in the first two blocks, both in the algorithms and the input signal they use. The first one uses the pitch [208] of the inertial sensor, while the second one uses the magnitude of the sensor's acceleration. We chose those two implementations because the different step detectors are suitable for different mounting points. The accuracy of step detection and the pedestrian's step length (SL) estimation determines the performance of position estimation methods. The final blocks of this proposed algorithm, i.e., heading estimation and position integration, were implemented as explained in [208].

Overall, the PDR-based method leverages the user's context to prevent "unnecessary GNSS activations," which is the primary goal for resource-constrained usage. We emphasize that all decision-making logic depends on on-device sensors; no external connectivity or infrastructure is necessary, making it suitable for environments with limited power and Internet access.

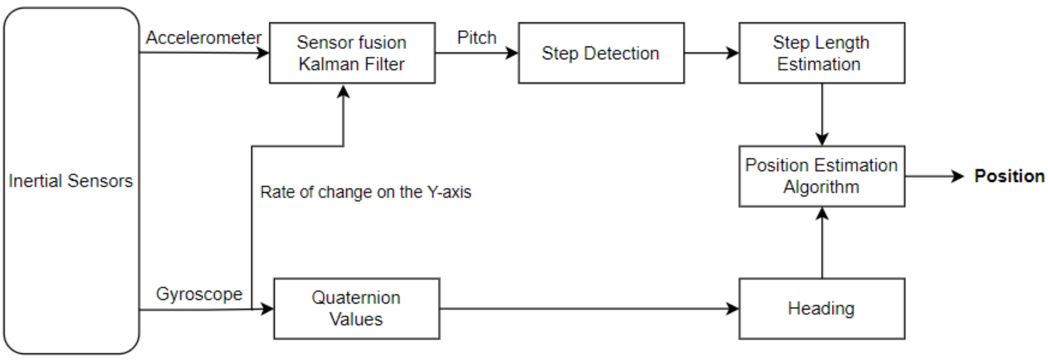


Figure 5.3: Pitch-based PDR implementation.

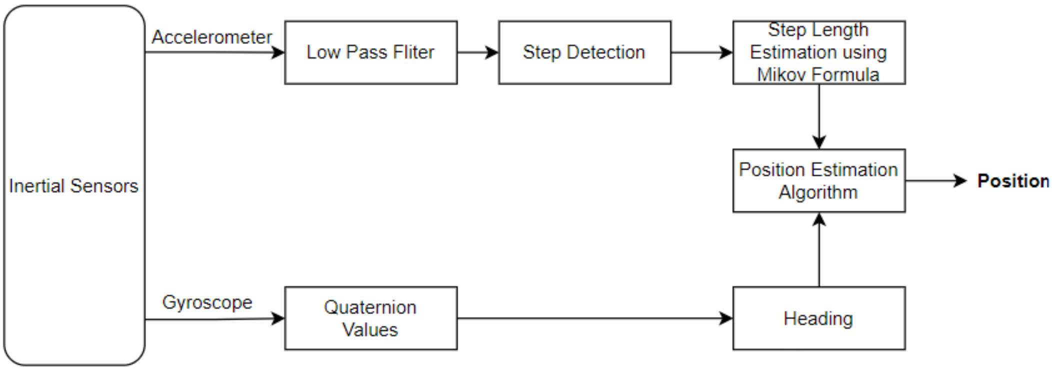


Figure 5.4: Acceleration-based PDR implementation.

5.2.3.1 **Pitch-based PDR implementation.**

Figure 5.3 represents the block diagram of the selected pitch-based PDR implementation, as explained in [208]. This proposed pitch-based approach detects steps using the pitch angle and estimates step length based on the pitch amplitude. We used a Kalman filter for the fusion of accelerometer and gyroscope [209] to calculate the roll and pitch of the inertial sensor. The step detection algorithm analyses the pitch and detects the step when local maximum and minimum pitch values occur in a certain interval. To avoid false step detection, the maximum and minimum values should be above or below a certain threshold, respectively.

Then, the step length is estimated using a first-order linear regression model on the pitch amplitude $(\Delta\theta)$:

$$SL = a \times \Delta\theta + b \tag{5.1}$$

where $\Delta\theta$ is the difference between the highest positive peak $(\theta_{\max})$ and the lowest negative peak $(\theta_{\min})$, in degrees. The constants b and a are the personalized parameters that fit each regression line.

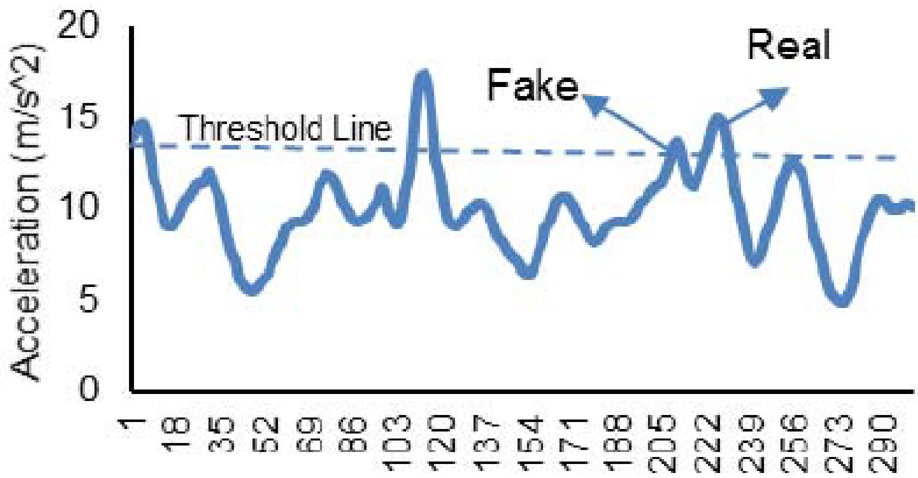


Figure 5.5: Fake vs Real peaks.

5.2.3.2 Acceleration-based PDR implementation

Figure 5.4 shows the second selected PDR implementation, which utilizes the acceleration values of the accelerometer sensor's X, Y, and Z axes to count steps in real time. Then, the magnitude value is calculated as the square root of the three accelerometer values, as shown in the equation below [208].

$$mag = \sqrt{x^2 + y^2 + z^2} \tag{5.2}$$

The magnitude value represents the vibration on the three-axis coordinates. The accelerometer sensors are inaccurate and suffer from various problems. Therefore, the derived data must be filtered to exclude noise and outlier values. In this work, the derived data were filtered using a low-pass filter. Smoothing the data helps improve the system's accuracy, as the accelerometer sensor is very sensitive to movements.

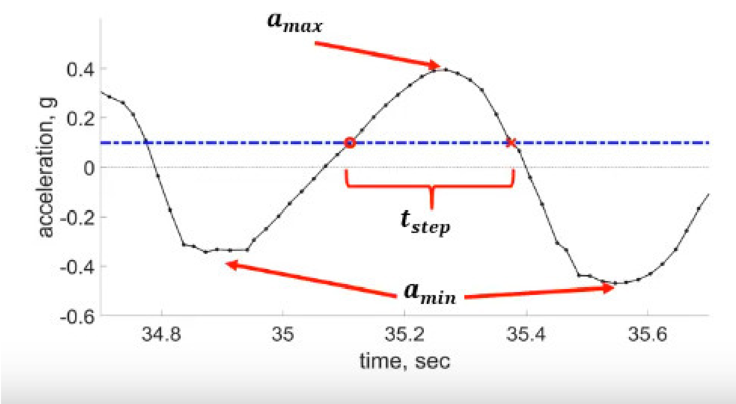


Figure 5.6: Acceleration chart.

Most current step detection algorithms rely on counting the peaks as each peak represents a user's stride. A significant problem is the fake peaks. A fake peak is a peak caused by an irrelevant movement. Fig. 5.5 shows the real and fake peaks. Counting the fake peak as a real peak increases the error in distance estimation. In this research, a peak detection method for the detection of the steps was used, as explained in [210], and the following Mikov formula was used to compute the length of the steps.

$$L_{Mikov} = K_5 \cdot t_{step} \cdot \sqrt[4]{a_{\max} - a_{\min}} \tag{5.3}$$

where $a_{\min}$ and $a_{\max}$ are the minimum and maximum acceleration values as shown in Figure 5.6, respectively, measured on the Z-axis in a single stride, t_{step} is step duration, and K_5 is a constant for unit conversion (i.e., feet or meters traveled).

5.3 Experimental evaluation

5.3.1 Experiments description

In our experiments, we try to show that using just acceleration or steps to activate the GNSS is not good enough, especially with human subjects. So, this work proposes a smarter and more efficient algorithm for GNSS activation, using the user position around their home, as demonstrated in the experiments we conducted. In our experiments, we assumed that the user's home was at the center of our defined geofence.

We conducted different experiments to assess the effectiveness of our proposed method, including experiments to evaluate the GNSS activation and the effect of position performance for the two PDR implementations. Two mounting positions were used to collect data, i.e., on the chest and in the swinging hands while walking.

A single volunteer (male, late 60s) acted as the test user in all experiments, wearing the device either strapped to the chest or held in one hand (to also examine the effect of placement). The volunteer began each trial at the center of the geofence (home position) and followed predefined movement paths marked on the ground (using cones) to ensure repeatability. We conducted five experiments in total – the first three focusing on GNSS activation logic and power use, and the last two examining the impact of PDR accuracy on the system:

(a). GNSS activation evaluation

Here, our GNSS activation method was compared with a basic method we implemented, inspired by work from the literature [196]. This simple system activates the GNSS whenever a step is detected. In this test, two evaluation metrics were used, i.e., when the GPS is activated/deactivated and power consumption.

(i). Experiment one: Walking continuously inside, outside, and back.

Walking continuously inside, outside, and back inside the safe zone: The volunteer walked continuously starting from the center of the safe zone, going beyond the 20 m radius, then turning around and walking back inside to the start point. This simulates a user leaving home and then returning shortly after. The walk was continuous without stopping. The purpose was to verify that our method activates GNSS only when the user is outside the safe zone and turns it off upon re-entry, saving some power compared to the other method.. In contrast, the acceleration-based method would keep GNSS on for the entire walk (since the user moves almost the whole time). We expected a single GNSS activation event in our system (during the outside portion) versus continuous activation for the acceleration-based method.

(ii). Experiment two: Walking continuously inside the safe zone.

Walking continuously inside the safe zone for at least 30 minutes (to simplify the experiments, we used 5 minutes). This scenario tests what happens if the user never leaves home but stays active. The objective of this experiment is to show that our method periodically activates the GPS if the user stays inside the safe zone, i.e., every 30 minutes, to refresh the position error accumulated by the PDR and the satellite data to avoid a cold start. We expected to see two GNSS activations (one at $\sim$5 min, one at $\sim$10 min) during the 14 min walk in our method, corresponding to these scheduled updates. This is in contrast to the acceleration-based method, which would treat the continuous motion as a reason to keep GNSS on constantly (resulting in much higher power draw). This experiment also demonstrates the periodic refresh mechanism (to avoid cold start and large drift) in action.

(iii). Experiment three: Walking and stopping inside, outside, and back inside the safe zone. This aimed to demonstrate that when the user stops moving outside, our system will shut off GNSS during the stationary period and reactivate it when motion or a step restarts. In this case, our method should turn on GNSS when the user first exits the geofence, turn it off shortly after the user comes to a stop outside, and then turn it on again when the walking recommences (until they re-enter the safe zone). The baseline, by comparison, would not immediately turn off GPS during a brief stop unless the no-motion persisted for the entire 10-minute timeout (which it did not in this test); therefore, the baseline (acceleration-based) effectively keeps GPS on throughout. This experiment thus highlights the finer power savings of our approach in actual usage: an elderly person might stop to rest, and our system can conserve energy in those moments, whereas a basic system would waste power needlessly.

This experiment aims to show that whenever the user stops outside the geofence, the GPS gets off until a motion/step is detected again.

(b). Effect of position performance

In this experiment, data were collected using two mounting positions: on the chest and in the hands.

(iv). Experiment four: Effect of length estimation and step detection.

In this experiment, the volunteer walked a straight route from the center, extending beyond the geofence and back, with each PDR implementation for two different mounting points. We repeated this route multiple times, using both PDR implementations (pitch-based and acceleration-based) and both device mounting positions (chest-mounted and handheld). This experiment aims to assess how the performance of step detection, step length estimation, and, therefore, position estimation affect the performance of the GNSS activation method. The idea is that certain combinations (e.g., pitch-based PDR on the chest) may yield a larger positional error. For instance, if step detection misses steps or misestimates distances, the system might believe the user left the safe zone earlier or later than they actually did. Consequently, "false" GPS activations could occur inside the geofence or delayed activations outside. By comparing the logged positions and GNSS trigger points, we assessed which PDR approach is more robust. This experiment revealed that the mounting position significantly affects PDR performance. For example, when using pitch-based PDR on the chest, the lack of pronounced pitch motion resulted in some missed or irregular step detections, causing positional errors to accumulate and periodically triggering GPS inside the zone (false positives). The same algorithm, when applied by hand (where pitch swings were clearer), performed much better, with the user's position correctly staying within bounds and no unwarranted GPS activation until the boundary was indeed crossed. Conversely, the acceleration-based PDR was more accurate on the chest (near the body's center) but degraded when in the hand (due to arm movement noise). These findings, detailed in 5, justify our choice to test two PDR methods and indicate that proper sensor placement is crucial for reliable performance. In an actual deployment, one would choose the PDR algorithm best suited to how the user carries the device (e.g., a wrist-worn device might behave more like a handheld case, in which pitch-based step detection proved advantageous).

(v). Experiment five: Effect of heading estimation

In the final experiment, the volunteer walked in a zigzag pattern (motion), starting at the home center and going out across the geofence, then coming back. This path involved frequent changes in heading direction (left-right turns) as the user moved forward. The goal was to investigate how errors in heading estimation impact the overall position solution and, consequently, GNSS activation. Without a magnetometer, our heading relies on integrating the gyroscope and occasional GPS corrections; over many turns, heading drift could cause the PDR to miscalculate the user's true position. In this zigzag test, we observed the end-to-end position error and verified whether the system still correctly recognized geofence exit and entry. The results showed that moderate heading drift did occur – the reconstructed path inside vs. outside had some offset – but our algorithm's periodic GPS correction (and final GPS fix when outside) mitigated any large error. The GNSS was activated at roughly the correct moments when the volunteer left and re-entered, indicating the method is tolerant to some heading error. This experiment demonstrates that while inertial-only tracking has limitations, the hybrid approach, with occasional GNSS calibration, effectively maintains the system's accuracy. It also reinforces the design decision to incorporate a periodic fix: without it, heading errors from prolonged IMU-only navigation could lead to either missed detections of exit or false triggers.

5.3.2 Data collection

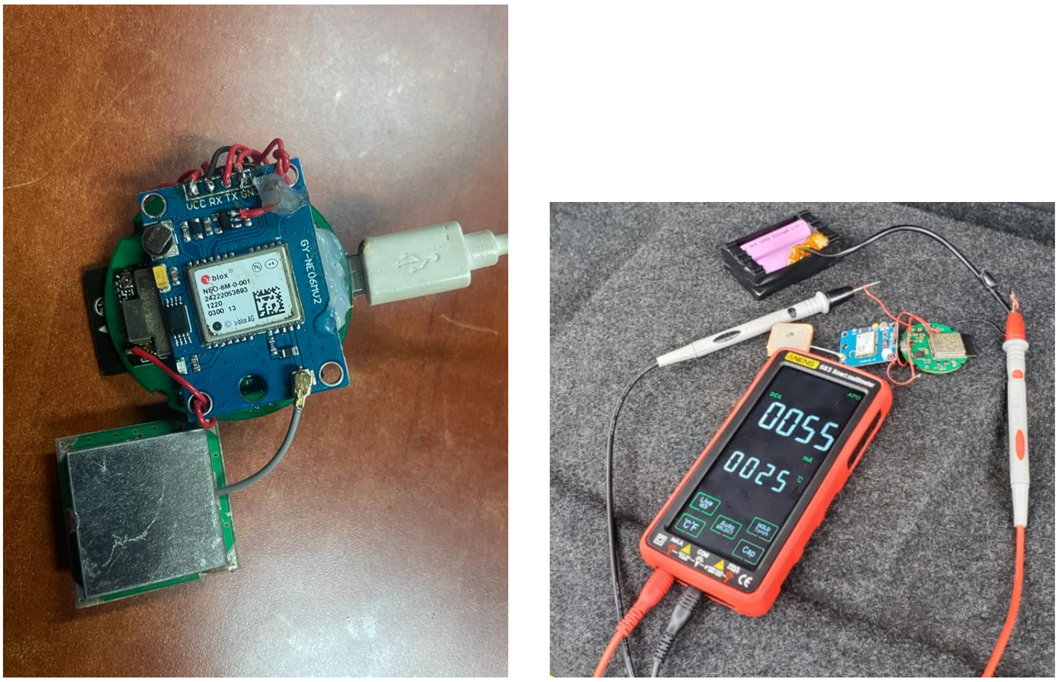
An embedded system on a custom-designed Printed Circuit Board (PCB) was designed and assembled for the tests as shown in Figure 5.7a. All experiments for the PDR-based GNSS activation method were conducted using a custom-built wearable localization device. A custom design allowed for the miniaturization of the system as it was intended to be carried or worn by the user. The PCB integrated the **ESP32 microcontroller** (ESP32 integrates a power amplifier, RF balun, an antenna switch, filter, low-noise amplifier, and power management module. The chip's sleep current is less 5 μA, making it suitable for battery-powered wearable electronic devices), **MPU6050 IMU** (a low-cost, low-power 6-axis motion tracking chip that integrates a

3-axis accelerometer, 3-axis gyroscope and a Digital Motion Processor (DMP) into a tiny 4 mm x 4 mm package), **NEO6 GPS** module (A u-blox module that was used to get the positioning information. This module only supports GPS, and its compact architecture, memory, and power options make NEO-6 modules excellent for battery-powered mobile devices with very strict cost and space constraints. It also comes with a small battery for hot-start and built-in EEPROM to save configuration settings when turned off), and **RAK3172 LoRaWAN** module in a tiny 40 mm diameter board and configured to operate at 868 MHz. It's an ultra-low-power consumption module with an active power consumption of less than 6 μA/MHz and 2.7 μA in sleep mode. The PCB also supports lithium-ion battery charging from the onboard USB connector for programming the microcontroller.

To emulate a rural, resource-constrained setting with minimal infrastructure and obstructions, tests were conducted on an open field (Makerere University rugby ground) characterized by scattered, inadequate, semi-structured buildings and minimal RF interference. This outdoor environment ensured good satellite visibility for reliable GNSS readings while representing the spatial layout of a rural homestead—a typical open compound with a few structures. This alignment with real-world use in resource-constrained areas made the experiments more relevant.

During data collection, the volunteer mounted the embedded system in the two mentioned mounting points and walked in the reference paths. This was done to test if the device could track the number of steps made, the distance traveled, and the user's position accurately, regardless of the device's mounting position. We define a circular geofence ("safe zone") with a radius of 20 m around the user's home for all tests. This radius was chosen to encompass the immediate vicinity of a typical rural home (e.g., house and yard), where an elderly user would typically move about. Movements within this 20 m safe zone are considered normal "at-home" activities that should not trigger continuous GNSS usage. In practice, the geofence size can be adjusted to each user's context (e.g., property boundary), but 20 m is a reasonable default for demonstrating our system. The user's home is assumed to be at the center of this geofence, as the initial GNSS fix at the home location establishes the origin for PDR tracking. By using the user's relative position within this geofence as the trigger, our method avoids the need for external infrastructure, such as beacons used in other work, which would be impractical in many low-resource environments that lack the means to install or maintain such devices. Instead, only the MPU6050 IMU sensor is used for tracking inside the geofence radius, eliminating dependency on external signals and aligning with the infrastructure-free requirement of resource-constrained settings.

The system printed out logs over a serial monitoring application; an Arduino serial monitor was used, after which the data was saved as a log of the experiment for analysis purposes. The logged data included current, relative location, number of steps made, heading of the person, and distance moved by the person. If the person has moved out of the specified geofence radius, the logs then include the status of the GPS and the current coordinates from it.



(a) PCB. **(b)** Current reading from multi-meter.

Figure 5.7: Designed embedded system.

To assess the power consumption, current readings were taken using a multimeter in series with the system and the battery. Measurements showed that with the GPS off, an average of 55 mA was drawn from the battery and 144 mA when the GPS was turned on, as shown in Figure 5.7b.

To evaluate the efficiency of our GNSS activation algorithm, we implemented a baseline method inspired by [196]. This simple activity-based approach relies solely on motion detection: it activates the GNSS receiver whenever the user is deemed “in motion” (detected walking) and deactivates it after the user has been stationary for a specified duration. In our implementation, a step detection triggers GNSS on, and if no motion is detected for 10 minutes, the GNSS is turned off. This reflects conventional duty cycling, where GPS is used only during movement. As prior studies have noted, however, such acceleration-based schemes cannot distinguish where the motion occurs – meaning any walking, even within one’s premises or house, would keep GPS active and drain power unnecessarily. This baseline represents the “naïve” solution our work seeks to improve upon.

5.3.3 Results and Discussion

Five experiments were conducted to evaluate the energy performance of our proposed GNSS activation method. Three were conducted to evaluate the GNSS activation, and two were conducted to assess the effect of position performance. The data was collected as explained in 5.3.2. The following represents the results and analysis of the experiments that were conducted.

(i). Experiment one:

Figure 5.9 represents the analysis of data collected in experiment one for a user walking continuously inside, outside, and back inside the safe zone, as illustrated in Figure 5.8. Figure 5.9a shows that the GPS was activated only once when the user briefly stepped out of the safe zone(section marked outside on the graph) and remained turned off for the entire period the user was walking in the safe zone (section marked inside). This demonstrates that our system turns on the GPS only when the user walks out of the geofence, maximizing the device’s battery life. Contrary, Figure 5.9b shows GPS continues to be turned on while the user moves, regardless of his/her position for the activity-based method.

(ii). Experiment two:

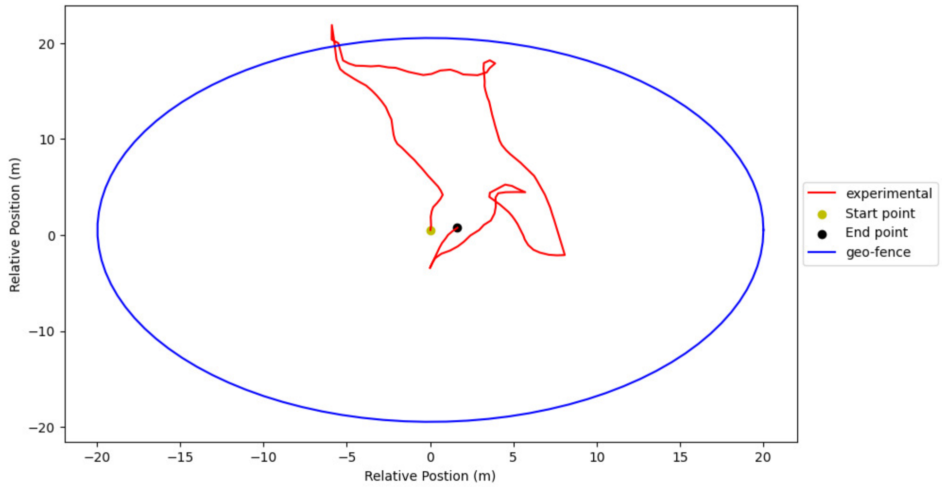
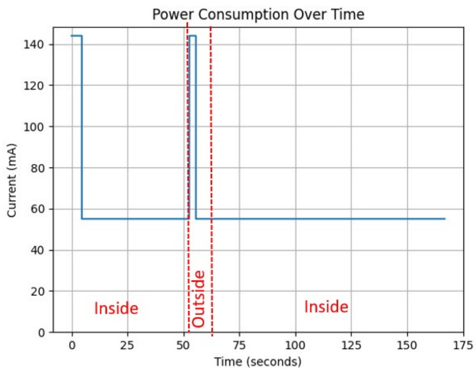
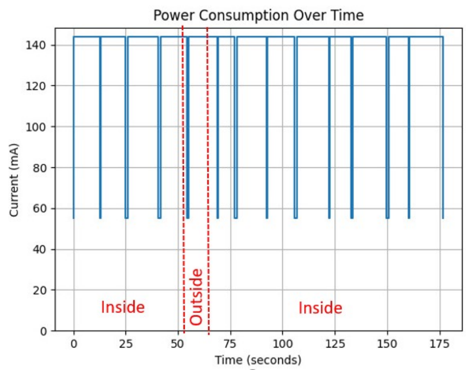


Figure 5.8: Shows the path taken by the volunteer during the experiment one.



(a) Power consumption of the proposed method.



(b) Power consumption of the activity-based.

Figure 5.9: GPS activation outside the geofence.

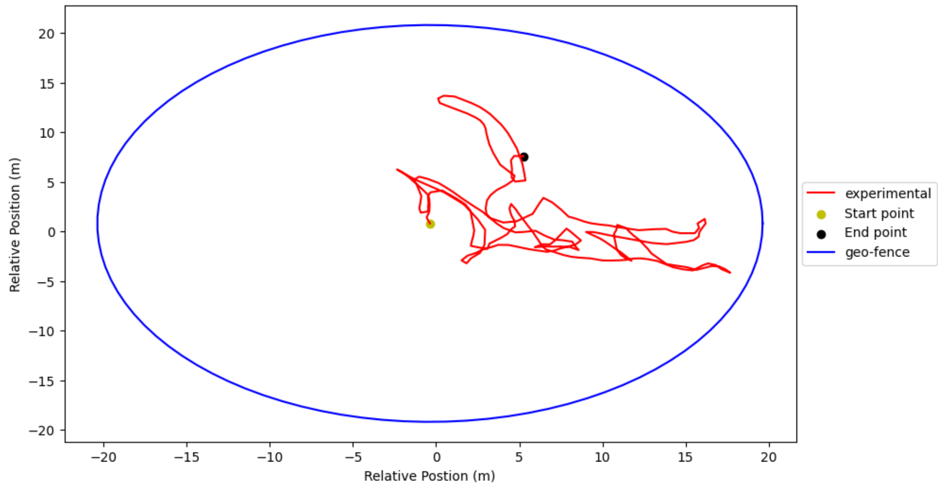
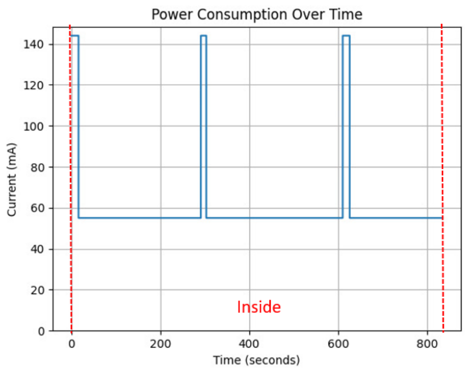
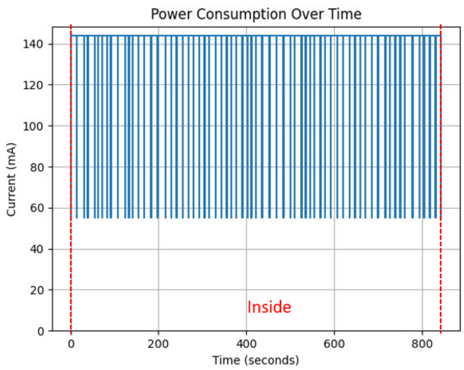


Figure 5.10: Shows the user movements and position for the 14 min walk in experiment two.



(a) Our method periodically activates the GPS if the user stays inside the safe zone to avoid a cold start.



(b) GPS continues to be turned on while the user moves in the safe zone for the activity-based method.

Figure 5.11: Periodic GPS activation within the geofence.

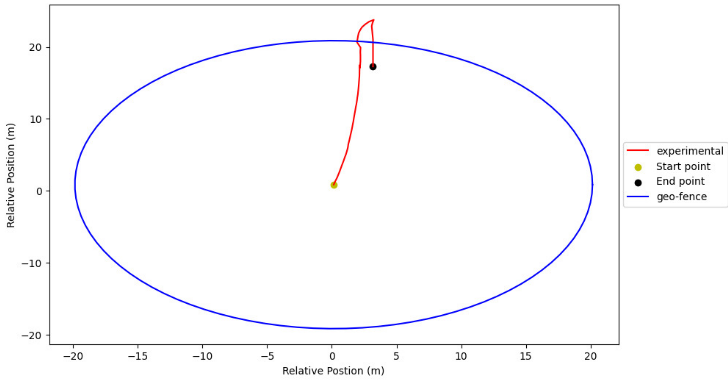
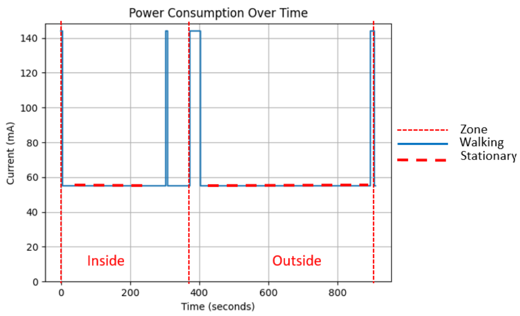


Figure 5.12: Shows the path taken by the volunteer during the experiment two.

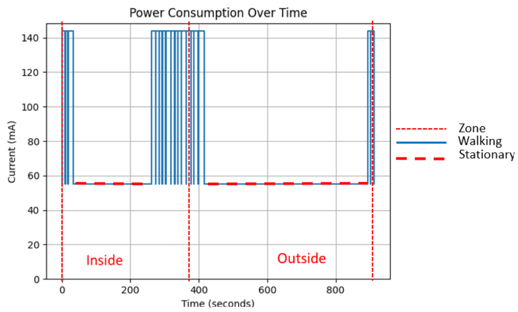
Figure 5.11 represents the analysis of data collected in experiment two, where the user walked continuously inside the safe zone, as illustrated in Figure 5.10. Figure 5.11a shows that the GPS was activated only two times each after approximately 5 minutes for 14-minute continuous walks within the safe zone. As already explained in 5.3.1, we used 5 minutes instead of 30 minutes to simplify the experiment. This periodic GPS activation is done to avoid a cold start of the receiver, as already explained in 5.2.2. Because of this periodic activation, GPS took an average of less than 14 seconds to get a position fix in most cases, hence less power consumption. Contrary, Figure 5.11b shows that the GPS continues to be turned on while the user moves, even though the user is inside the safe zone, hence unnecessary power consumption.

(iii). Experiment three:

Figure 5.13 represents the analysis of data collected in experiment three, where the user walked and stopped inside, outside, and back inside the safe zone, as represented in Figure 5.12. This experiment demonstrates that in our method, the GPS is turned off whenever the user is stationary until a step is detected again when the user is outside the geofence, as shown in Figure 5.13a. Power consumption for both systems is comparable when the user is stationary regardless of user position but very high for the activity-based system when the user moves even though inside the geofence, as illustrated in Figure 5.13b.



(a) Shows GPS is turned off whenever the user is stationary even though outside the safe zone.

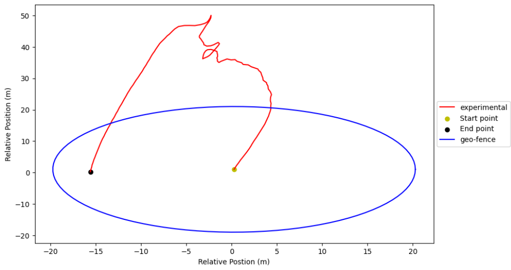


(b) Shows that GPS is turned on and off for all times apart from when the user is stationary.

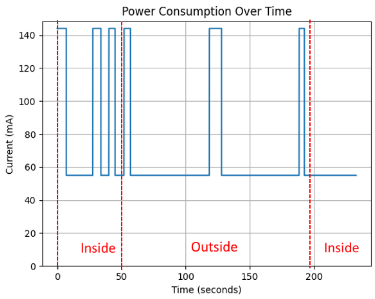
Figure 5.13: GPS activation outside the geofence.

(iv). Experiment four:

Figure 5.14 shows the user positions estimated using pitch-based PDR implementation mounted on the chest. In this experiment, the user walked straight inside, outside, and back inside, as illustrated in Figure 5.14a. This was done to demonstrate the effect of step detection and length estimation performance on the GPS activation method. Figure 5.14b shows several unnecessary GPS activations inside the safe zone resulting from wrong PDR positioning because of the mounting point used. On the contrary, the same PDR implementation has a better positioning and even better power optimization when a different mounting point is used, as demonstrated in Figure 5.15. Similarly, better positioning and power optimization are achieved as illustrated in Figure5.16 where acceleration-based PDR implementation is mounted on the chest, but contrary for the same implementation when the device is carried in the hands as shown in 5.17 From analysis it is clear the pitch-based PDR implementation works best with the body's swinging parts, but the acceleration-based method does not.

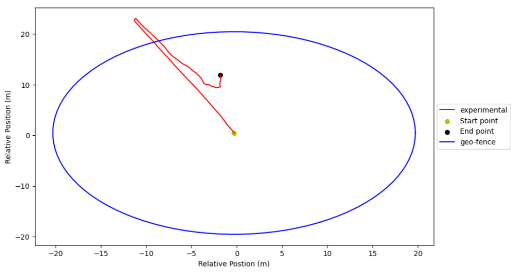


(a) Shows user movement and position in the Pitch-based PDR implementation when the device is worn on the chest.

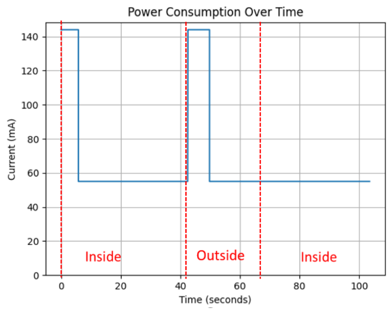


(b) Unnecessary GPS activations due to poor position performance in the Pitch-based PDR implementation when the device is worn on the chest.

Figure 5.14: User position and power consumption using Pitch-based PDR implementation with the device on the chest.

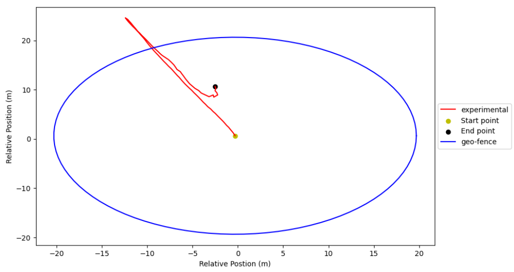


(a) Shows user movements and position in the Pitch-based PDR implementation with the device in hand.

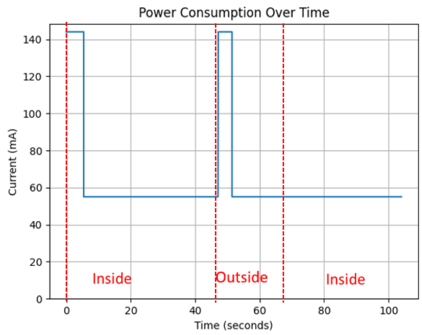


(b) GPS activations resulting from accurate position performance in the Pitch-based PDR implementation with the device in hand.

Figure 5.15: User position and power consumption using Pitch-based PDR implementation with the device in hand.

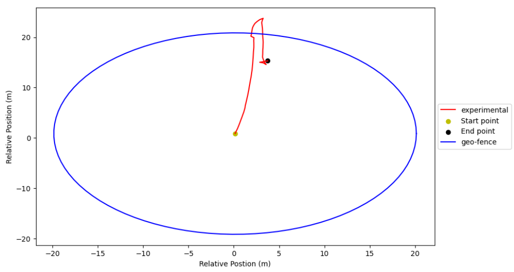


(a) Shows user movements and position in the Acceleration-based PDR implementation with the device on the chest.

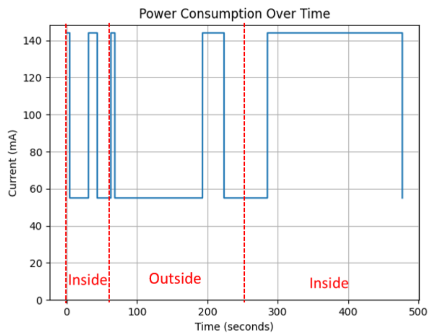


(b) GPS activations and power consumption resulting from accurate position performance in the Acceleration-based PDR implementation.

Figure 5.16: Shows the user position using Acceleration-based PDR implementation with the device on the chest.

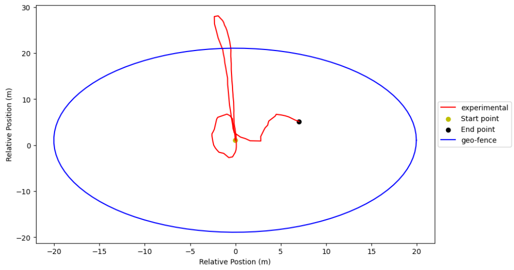


(a) Shows user movements and position in the acceleration-based PDR implementation with the device in hand.

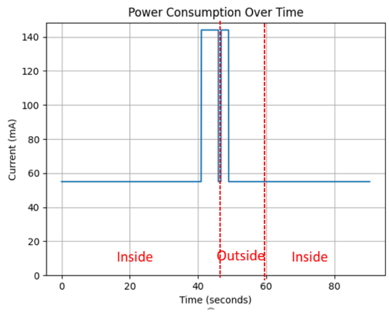


(b) Unnecessary GPS activations resulting from poor position performance in the acceleration-based PDR implementation.

Figure 5.17: Shows the user position using Acceleration-based PDR implementation with the device in hand.



(a) Shows the effect of heading estimation on the final user position.



(b) shows the GPS was activated when the user was still in the safe zone.

Figure 5.18: Shows the effect of heading estimation on the user's final position estimation and power consumption.

(v). Experiment five:

Figure 5.18 shows the effect of heading estimation on the user's final position estimation and power consumption. The acceleration-based PDR implementation mounted on the chest was used in this experiment, and the user walked in a zigzag from the center of the geofence to the outside and back to the center, but because of the effect of heading estimation, the user position was off by more than 3 meters. Figure 5.18b shows the GPS was activated when the user was still in the safe zone, hence unnecessary power consumption.

A critical aspect of these experiments is power usage, as our aim is to extend battery life. We measured the device's current draw in different states. Figure **??** shows a multimeter reading of the system's current: approximately 55 mA when the GNSS module is off (only the MCU and IMU active) and about 144 mA when GNSS is on. This nearly 3× increase when GPS is active quantifies the heavy power cost of continuous GNSS in a wearable and aligns with known estimates for GPS power consumption in smartphones and IoT devices. Therefore, minimizing the time spent at 144 mA is crucial. In our logs, we tracked the cumulative duration that GNSS was powered in each scenario, and from that, we extrapolated relative energy use. The results above showed that our position-based method significantly reduced active GPS time. For example, in Experiment 1, our method turned on GPS only once briefly when the user stepped just outside the 20 m boundary, whereas the acceleration-based method kept it on nearly the entire time the user was walking. In short, the experimental evidence supports that using user position (via PDR) as the trigger is far more energy-efficient than using raw motion or periodic updates alone, especially in scenarios where the user spends a lot of time around home (which is typical for the elderly population we target).

5.4 Conclusion

This chapter has presented a position-based GNSS activation method using a PDR system as the main input source. The aim is to design an activation method that is better than usual activity-based methods for pedestrians (commonly acceleration-based) and cheaper than common position-based methods requiring beacons. From all experiments and results, our proposed method shows better power optimization (by more than 50%) compared to the activity-based method, as demonstrated using the current draw.

The proposed GNSS activation and position update rate method depends on the user position estimated by the PDR system. So, the accuracy with which the PDR system determines the position is key to the effectiveness of our proposed method. To assess this, two different PDR systems were implemented and evaluated, i.e., acceleration-based and pitch-based PDR implementation. Two mounting positions, i.e., on the chest and in the hands, were used to collect data. The experimental evaluation confirmed that the PDR's estimated position directly affects the proposed GNSS activation method, reducing its performance.

The approach defined in this chapter can be applied to monitoring children and pets in open-space scenarios such as homes, sports fields, and recreation parks.

CHAPTER

6

ML-Driven User Activity-Based GNSS Activation

6.1 Introduction

Chapter 5 presented a position-based GNSS activation method using a PDR system as the main input source. This method does not need to install beacons in user premises, making it suitable for a resource-constrained environment, especially in poor rural areas of Africa with poor housing infrastructure. The implemented PDR method was based on the definition of a geofence around the user's home such that the GNSS is only turned on when the user's position is estimated to be outside the geofence (safe zone). Although the position-based PDR approach, as presented, proved to be a viable method for monitoring elderly people in a resource-constrained environment as it offers an infrastructure-free, efficient, and cost-effective solution, it is still partially limited by the accuracy of the PDR system in estimating the user's position as the accuracy with which the PDR system determines the position is key to the effectiveness of the proposed method. Position estimation in PDR systems is often challenged by cumulative errors, which tend to grow over time, reducing the accuracy of the estimated position [211]. Therefore, in this chapter, we explore a different approach leveraging machine learning (ML) to improve the effectiveness of GNSS activation.

As discussed in chapter 4, varying the position update frequency and/or deciding when to turn on/off the receiver based on the user context is one of the main types of power optimization. There are two main types of context triggers: the user position and the user activity. The user position-based method often relies on deploying beacons, such as Bluetooth or infrared devices, at specific locations to detect where it is unnecessary to activate the GNSS receiver. While this approach optimizes power consumption by minimizing GNSS use, it is impractical for resource-constrained settings due to the significant costs involved in acquiring, installing, and maintaining beacons, as well as ensuring a stable power supply and connectivity. Many rural and low-income areas lack reliable electricity and face financial limitations, making beacon-based infrastructure unsustainable. Furthermore, the scattered and informal structure of homes in such areas complicates effective beacon placement.

The activity-based method usually detects moving or walking activity through sensors such as accelerometers. While this approach can effectively manage GNSS activation for objects with predictable and less erratic movement patterns, such as bicycles or cars, it presents significant challenges when applied to human subjects. Humans naturally exhibit complex, frequent, and often irregular movements during everyday activities, such as walking around the home, standing up, sitting down, or even minor adjustments in posture. The system can misinterpret these frequent and varied movements as activities that necessitate GNSS activation, leading to a high number of false alarms where the GNSS is activated unnecessarily. Such misinterpretations reduce the system's overall efficiency and result in significant battery drain, defeating the goal of optimizing power consumption.

In remote, resource-constrained environments, people spend most of their time outdoors around their houses, where it is unnecessary to activate the GNSS so frequently to monitor them. Restricting the GNSS activation to the moments when they are moving to a different location (walking away from home) could be enough and would reduce power consumption. For that, it is necessary to distinguish the shorter and more chaotic walking associated with home activities from the longer and more regular walking associated with a translation.

Therefore, this Chapter introduces a novel ML-driven GNSS activation method that explicitly detects the “walking away” activity class, distinguishing actual departures from home from routine household movements—an aspect overlooked in previous works. Unlike conventional methods that rely on motion thresholds, costly beacon installations, or HAR models, which focus on general movement states, the proposed system is designed to operate effectively in resource-limited settings without requiring additional infrastructure. This distinction is particularly relevant and essential for applications intended for elderly monitoring in rural resource-constrained environments, where GNSS activation should only occur when a person genuinely leaves their usual environment. We explore various ML-driven methods with the aim of creating a smarter system that reduces false activations and achieves higher power efficiency, enhancing the overall applicability of remote monitoring in resource-constrained environments. The key contributions of this chapter are:

- An optimized GNSS activation method based on detecting the ”walking away” activity.
- An evaluation of four machine learning models—LSTM, XGBoost, SVM, and Random Forest—highlighting trade-offs between accuracy and computational efficiency.
- A real-world validation of a built low-resource embedded system based on our proposed GNSS activation method in a rural, resource-constrained setting, demonstrating over 40% power savings compared to existing methods.

Acceleration and gyroscope user data were collected during the experiments, and four ML classification models (i.e., RF, LSTM, SVM, and XGBoost) were used for training and testing. The best model, XGBoost, was exported to a custom-designed embedded system and evaluated in real-world tests, demonstrating over 50% energy savings compared to conventional motion-based methods.

The rest of this chapter is organized as follows: Section 6.2 describes the proposed methodology and materials. Section 6.3 presents details about the experiments, their results, and discussion. Finally, Section 6.4 summarizes and concludes this chapter.

6.2 Material and Methods

We introduce a novel GNSS activation method based on user activity. The core idea of our proposal is detecting the activity ”walking away from home,” and this approach harnesses the power of ML to discern between user motion modes at home and when moving to a different location. The differentiation of these user motions is based on primary datasets that characterize different types of movements associated with various home user activities, such as sitting, standing up, walking from one room to another, washing dishes, etc. Our focus is not on classifying user activities, such as those in human activity recognition, but rather on determining whether the user is walking away from home.

Unlike the methods reviewed in the previous chapters, we hypothesize that detecting the activity of ”walking away from home” is sufficient for resource-constrained environments, as this approach eliminates the need for beacons, avoids assumptions about varying signal strengths indoors and outdoors, is better than just basic acceleration signal thresholding, and is simpler than human activity recognition since we do not need to classify different daily user activities.

The objective of this section 6.2 is to present the selection criteria of a classification model that is good enough to be implemented and validated in a real device and experiments. Next, inertial data collection, data pre-processing, features engineering, and the classification model selection will be described, where four common classifiers will be evaluated: RF, LSTM, SVM, and XGBoot.

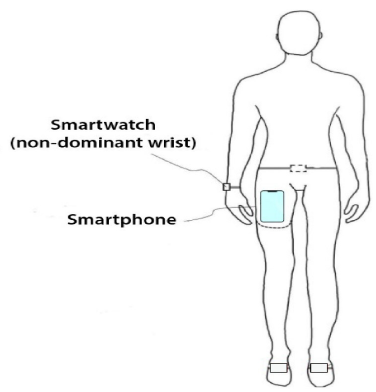


Figure 6.1: Experimental setup.

6.2.1 Data collection

The data collection process was facilitated by Sensor Logger [212], a free, easy-to-use, cross-platform data logger installed on a smartwatch worn on the non-dominant wrist, as illustrated in Figure 6.1. This application logged readings at a sampling frequency of 100 Hz from the accelerometer and gyroscope sensors during the experiment. The smartwatch was connected to the smartphone, which served as a data storage device for the recordings captured during the process. The hardware used in this experiment was the iPhone 12 series and an Apple Watch Series 7. We recognize that our system is intended for resource-constrained environments; however, the choice of the hardware for data collection was primarily due to their availability in the lab at the time of the experiments. However, this choice does not impact the generalization of the resultant model when embedded on a low-cost device, as demonstrated in Section 6.3. For this study, the device on which the model was embedded runs on an ESP32 microcontroller for validation in real-world experiments.

Data was collected in a simple natural home environment to accurately represent user activities in resource-constrained home environments and as the participant walked away from home to work to represent movements away from home. For the walk from home to work, participants made short stops to simulate typical everyday situations in the local low-resourced area when the elderly people pause to greet other passersby, a common occurrence in these environments.

Two elderly participants—a female aged 72 and a male aged 70—participated in the data collection process. The experiments were conducted daily for two weeks (10 working days) at their homes. Each day, both participants were recorded for 20 minutes while performing activities at home, such as sitting, sleeping, washing utensils, standing, or moving from one room to another, and another 20 minutes while walking away from home ($\sim$ 800 minutes of recordings). Our ground truth was raw data labeled ”at home” and ”walking away” from home based on human observation. These classes represented data collected during the user’s activities around the home and while walking away from home, respectively.

6.2.2 Data pre-processing

6.2.2.1 Data Filtering

Most of the energy of the inertial signals during human activity is in the frequency band of 0-20 Hz [213, 214, 215, 216]. Therefore, we filtered the six acceleration and angular rate signals to make the signal segmentation and subsequent computational steps more robust. We applied two zero-phase 5$^{\text{th}}$-order Butterworth filters: one high-pass filter with a cut-off frequency at 0.5 Hz and another low-pass filter with a cut-off frequency at 20 Hz.

6.2.2.2 Signal Vector Magnitude

Each of these sensors provides data in three dimensions: the x-axis, y-axis, and z-axis. Orientation changes can impact the recognition performance of these sensors, resulting in a drop in performance if the classification algorithms were trained only for a specific orientation [217]. To mitigate the effects of orientation changes, we added a fourth dimension to each sensor's existing three dimensions, referred to as the sensor's magnitude.

The acceleration vector magnitude is calculated from the acceleration's three orthogonal components (x, y, z). The formula is:

$$a_{mag} = \sqrt{a_x^2 + a_y^2 + a_z^2} \tag{6.1}$$

Where a_x, a_y, and a_z are the acceleration signals along the x, y, and z-axis, respectively.

Similarly, the gyroscope vector magnitude is calculated from the angular velocity's three orthogonal components (x, y, z). The formula is:

$$w_{mag} = \sqrt{\omega_x^2 + \omega_y^2 + \omega_z^2} \tag{6.2}$$

Where ω_x, ω_y and ω_z are the angular velocity signals along the x, y, and z-axis, respectively.

Magnitude signals are related to the movement intensity as they account for the overall movement. Figure 6.2 presents a visual example of accelerometer magnitude data collected during user activities around the home and while walking away from

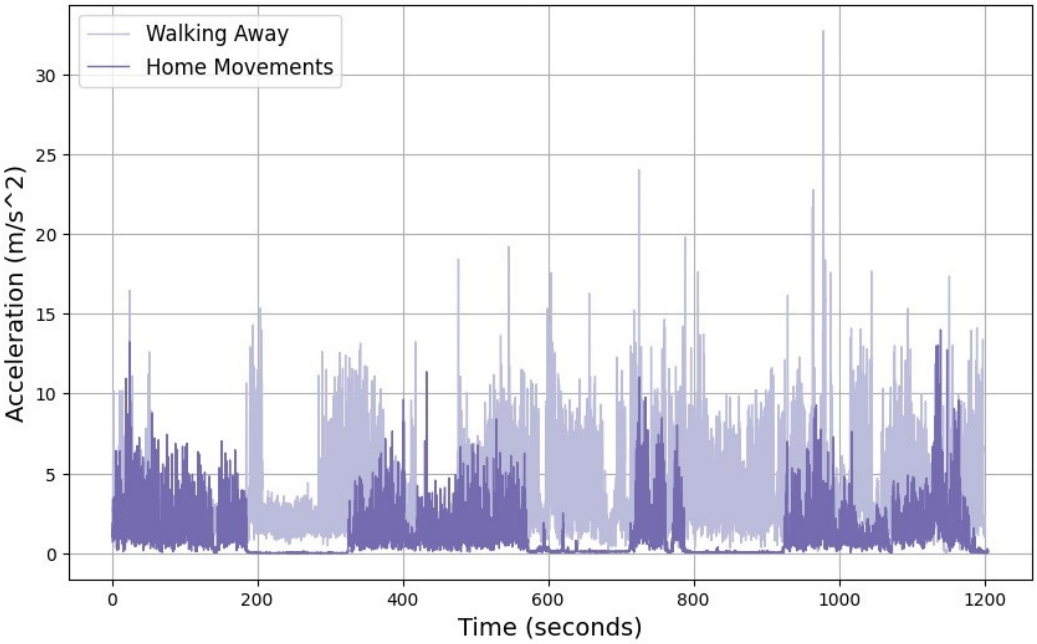


Figure 6.2: Presents a visual example of accelerometer magnitude data collected during user activities around home and while walking away from home.

home. It clearly illustrates the difference in movement intensity. The intensity of the accelerometer data is notably higher during the "walking away from home" activity, with frequent peaks reaching up to 30 m/s², indicating strong, continuous motion and higher physical effort. Most values remain above 5 m/s^2, showing consistent, vigorous activity typical of walking at a steady or fast pace. In contrast, the "home movements" activity exhibits much lower intensity, with most values between 0 and 10 m/s² and only occasional peaks around 10 to 15 m/s^2, reflecting lighter, intermittent movements such as walking indoors or short, less strenuous actions.

6.2.2.3 **Data segmentation**

In order to facilitate effective feature extraction, a fixed-size overlapping sliding window segmentation technique was used. The signals were split into windows of a fixed size of 5 seconds with a 50% overlap. This was applied to the entire dataset to provide context about the features' behavior over time.

Although a 1–2 second window size has proven to provide the best trade-off between human activity recognition speed and accuracy [218], in our case, we selected a 5 second window because our experiment was not highly controlled, and the participants did not strictly perform one activity. This implies that data variations based on human participants' gait and motion will ideally represent various activities if a smaller time window is used. Our experiments use data collected in 5 seconds and are pre-processed and feature-engineered to provide a better generalization for a dominant activity. Also, the models need to better identify subtle variations in the data, which are important for distinguishing between activities with similar short-term characteristics that differ over a longer period. For example, it is difficult to discriminate between walking around home and walking away from home in a data window of 1 second.

Table 6.1: Some of the statistical features selected. *P* is the probability of an occurrence of each of the values in x_i, and *S* represents the signal components along the x, y, and z-axis

Feature	**Equation**
Standard deviation	$\sigma = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(x_i - \bar{x})^2}$
Median	$M = \left(\frac{3n-cf}{f}(\omega) + L_m\right)$
Kurtosis	$KV = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{x_i-\bar{x}}{\sigma}\right)^4$
RMS	$\text{RMS} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2}$
Energy	$\epsilon = \sum_{i=1}^{N} \lvert x_i \rvert^2$
sma	$sma_{xyz} = \frac{1}{3}\left(\sum_{j=1}^{N}\lvert x_i\rvert + \sum_{j=1}^{N}\lvert y_i\rvert + \sum_{j=1}^{N}\lvert z_i\rvert\right)$
Skewness	$SV = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{x_i-\bar{x}}{\sigma}\right)^3$
Entropy	$E = \sum_{i=1}^{n} P(x_i)\log_2 P(x_i)$

6.2.2.4 **Downsampling**

The data were captured at a sampling rate of 100 Hz and subsequently downsampled to 10 Hz. This was done due to the ESP32 microcontroller's memory and power computing limitations, which we used in our embedded system for experimental purposes.

6.2.3 Feature engineering

In general, feature extraction corresponds to a data transformation process performed on the segmented data. In the context of inertial sensors, this process is necessary because the raw data are not suitable for use by conventional ML algorithms [219].

This study extracted time and frequency domain statistical features on a per-time window basis for the magnitude signals and each axis of the tri-axial accelerometer and gyroscope. Time domain features, such as mean, standard deviation (σ), max, min, angle, meanFreq, root mean square (rms), median, variance, kurtosis, interquartile range (irq), signal magnitude area (sma), and mean absolute deviation (mad); and frequency domain features, such as entropy (E), bandsEnergy, maxInds, skewness, and energy (ε), among others, were investigated in this study. Most of the features are well-known statistics. Table 6.1 contains the definitions of some of them.

6.2.4 Classification model selection

The aim of this chapter is to validate the hypothesis that detecting ”moving away from home” is a suitable method for activating GNSS in resource-constrained environments. For this, we need a good classification model, but our goal is not to find the best possible model but to make a first proof of concept. Therefore, in this subsection, we will consider four common models in the field of human activity recognition [220, 221, 222, 223], evaluate them, and select the best one.

6.2.4.1 Classification models

In this subsection, we briefly describe the classification models used in this study: RF, SVM, LSTM, and XGBoost.

RF generates an ensemble of multiple decision trees to achieve a single, more accurate prediction or result. It is a versatile and computationally efficient algorithm capable of processing large datasets rapidly, is easily adaptable to various ad hoc learning tasks, and returns measures of variable importance [224]. RF is widely used for classification tasks, including the classification of human activities [225].

XGBoost, like RF, is an ensemble learning algorithm based on decision trees, but they have significant differences in how they build and use these trees. XGBoost develops one tree at a time, correcting faults caused by previously trained trees, in contrast to RF, where each tree is generated independently, and the results are aggregated at the end. Trees are planted until none remain [226]. The model uses a gradient descent algorithm to minimize the loss when adding new models. This sequential addition of weak learners (trees) ensures that the shortcomings of previous trees are corrected [227].

SVM is based on mapping datasets to higher dimensions, making it easier to separate data points. By adding higher dimensions, kernel functions simplify the boundaries for non-linear problems, facilitating the separation of complex data points [228]. SVM has emerged as a potent pattern recognition tool over the past decade and has been applied to human activity recognition problems [229, 230].

LSTM is a type of deep learning sequential neural network designed to allow information to persist over time. LSTMs excel in processing and analyzing sequential data types like time series, text, and speech. These properties make LSTM outperform traditional ML methods in recognizing various user activities [231].

6.2.4.2 **Model selection procedure**

The procedure for selecting a classification model involved first evaluating the four models using all features. Then, they were evaluated using only the 10 features that contributed the most to each model, as determined by the SHAP [232] method. Based on the results of both evaluations, a classification model was selected and then implemented in the embedded system. This two-step evaluation process ensures that the chosen model is both accurate and efficient for real-world applications.

6.2.4.3 **Implementation and training**

We implemented the four models using Python-based learning frameworks, specifically, TensorFlow and Scikit-learn. TensorFlow and Scikit-learn are two of the most widely used Python libraries for ML[233]. Scikit-Learn is best suited for traditional ML tasks, offering simplicity and a wide range of algorithms. On the other hand, TensorFlow excels in deep learning, providing scalability, flexibility, and tools for deploying production-ready models[234].

Two elderly participants were recorded for 10 days, each for 40 minutes per day (20 minutes at home and 20 minutes walking away from home) at a sampling rate of 10 Hz, resulting in approximately 480,000 samples for each of the 6 signals (accelerometer x, y, z, and gyroscope x, y, z). We then computed the magnitude of both the accelerometer and gyroscope across the x, y, and z axes, creating 8 total signals of 480,000 samples each. From these, we selected 5 signals for further analysis: Acceleration Vector Magnitude, Gyroscope Vector Magnitude, and Gyroscope X, Y, and Z. The individual x, y, and z signals of the accelerometer were excluded because their contributions are largely represented in the Acceleration Vector Magnitude. The vector magnitude of acceleration captures the overall movement intensity while reducing computational complexity by simplifying the data into a single scalar value. The Gyroscope X, Y, and Z signals were selected to preserve detailed rotational information. Angular velocity, particularly along individual axes, can help differentiate between subtle variations in activities, such as changing direction. A 5-second window was used to generate records, resulting in approximately 9,600 records of 5 signals. For each signal, 17 features were computed, creating a dataset of around 9,600 records with 85 features/record.

During the evaluation, 80% of the data was used for training and 20% for testing. The 80-20 split is a well-established practice that ensures a balance between having enough data to effectively train the model and using a sufficient portion for testing to assess the model's generalization capabilities.

Several standard evaluation metrics were used in our experiments to measure our models' performance, including precision, recall, and F1-score [204]. These were derived from the confusion matrix (Table 6.2) and applied to the classifier evaluation, as shown in Equations 6.3 to 6.5.

Precision is a measure of the accuracy of positive predictions by the ML algorithm, and it is given by equation 6.3:

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{6.3}$$

While recall measures the proportion of actual positive cases that are correctly identified by the algorithm. It is given by the equation 6.4:

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{6.4}$$

Table 6.2: Confusion Matrix.

	Actually Positive (1)	Actually Negative (0)
Predicted Positive (1)	True Positives TPs)	False Positives (FPs)
Predicted Negative (0)	False Negatives (FNs)	True Negatives (TNs)

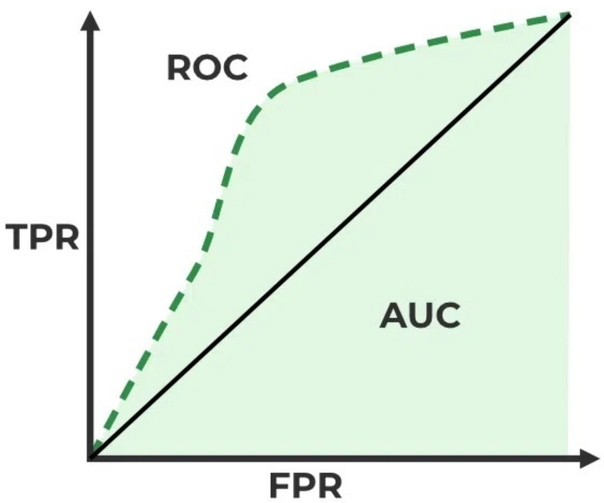


Figure 6.3: ROC curve showing the TPR vs. FPR, with AUC as an indicator of model performance [235].

F1-score is the harmonic mean of precision and recall, a more informative model performance evaluation metric than accuracy, given by equation 6.5:

$$\text{F1-score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{6.5}$$

We also computed the overall accuracy scores for the models, a metric that measures how often an ML model correctly predicts the outcome given by equation 6.6:

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \tag{6.6}$$

Additionally, the area under the receiver operating characteristic (ROC) curve was measured. This metric is widely regarded as the standard for comparing performance. The ROC curve illustrates the optimal decision boundaries by plotting the true positive rate (TPR) against the false positive rate (FPR), as defined in Equations 6.7 and 6.8:

$$\mathrm{TPR} = \frac{\mathrm{TP}}{\mathrm{TP{+}FN}} \tag{6.7}$$

$$\mathrm{FPR} = \frac{\mathrm{FP}}{\mathrm{FP} + \mathrm{TN}} \tag{6.8}$$

As illustrated in Figure 6.3, the area under the ROC curve (AUC) is widely used to evaluate classifier performance. The AUC value ranges from 0.0 to 1.0, with 1.0 indicating perfect prediction, 0.5 indicating random prediction, and values below 0.5 considered poor predictions [236].

6.2.4.4 **Evaluation using all the features**

This subsection presents model performance (classification) results when all 85 features were used, and the performance comparison of different models on the whole dataset is presented in Table 6.3.

LSTM and XGBoost outperform SVM and RF in detecting whether a user is walking away from home. LSTM achieves the highest performance across all metrics, with a precision and recall of 0.98, an F1-score and accuracy of 0.98, and an AUC of 0.96. XGBoost follows closely with strong precision (0.96), recall (0.94), and AUC (0.97), highlighting its effectiveness in classifying complex activity patterns. RF shows decent results (0.92 for precision and F1-score) but lags behind LSTM and XGBoost. With the lowest performance (accuracy and recall of 0.84), SVM struggles to classify the activities.

Overall, the results demonstrate that models such as LSTM and XGBoost, which are better at handling sequential data and complex relationships [226, 237], are better suited for activity classification tasks in dynamic environments like detecting a user walking away from home. These results were refined through a SHAP feature selection process, which will be discussed in the next subsection.

Table 6.3: Performance comparison of different models on the whole dataset.

	Metrics	SVM	XGBoost	RF	LSTM
On the whole dataset	Precision	0.85	0.96	0.92	0.98
	Recall	0.84	0.94	0.91	0.96
	F1-score	0.85	0.95	0.92	0.98
	Accuracy	0.84	0.96	0.91	0.97
	AUC	0.85	0.97	0.93	0.96

6.2.4.5 Evaluation using selected features

Datasets are often highly dimensional, containing a large number of features, although the relevancy of each feature for analyzing this data is not always clear [238]. Since not all features contribute equally to activity classification, the type and number of features required to perform a given classification task successfully depend on the discriminatory qualities of the features. By involving fewer features in the classification process, the required computational effort (time) and memory are reduced. This requirement is essential in this study since the best model will be exported to an embedded system with limited memory and processing power to test and evaluate our model in a real/natural environment. Also, including every feature creates multiple dimensions, leading to an overfitting problem [239].

To mitigate overfitting caused by extraneous dimensions, we used SHapley Additive exPlanation (SHAP) [232], a technique that helps understand how individual features influence a model's output. By leveraging the interpretability of SHAP values, we were able to identify and select the most significant features, potentially reducing the feature space while maintaining or even enhancing model performance. Figure 6.4 shows the SHAP analysis conducted on the XGBoost model, illustrating each feature's impact on predictions.

In Figure 6.4, red dots represent features that had a significant impact on model output, while blue dots indicate features with less impact. We used SHAP values to identify the ten most important features and retrained all models with this reduced feature set. The results obtained using only the selected features (10 first features) are presented in Table 6.4.

Table 6.4: Performance comparison of different models on selected features.

	Metrics	SVM	XGBoost	RF	LSTM
On selected features	Precision	0.87	0.98	0.92	0.98
	Recall	0.86	0.97	0.92	0.97
	F1-score	0.85	0.97	0.93	0.98
	Accuracy	0.85	0.97	0.93	0.98
	AUC	0.88	0.97	0.97	0.98

6.2.4.6 **Selected model**

In this subsection, we discuss the results based on selected features applied to the four models used in this experiment.

From the performance on the selected features as shown in Table 6.4, XGBoost and LSTM demonstrate exceptional accuracy, precision, recall, and F1 scores, making them top contenders. In terms of AUC, as illustrated in Figure 6.5, the LSTM model delivered the best performance with an AUC of 0.98, showcasing its strong ability to distinguish between ”user at home” and ”user walking away” activities. Similarly, XGBoost performed exceptionally well with an AUC of 0.97, proving nearly as effective as LSTM in classifying user activities.

XGBoost showed improved performance on the selected features compared to the entire dataset, as evidenced by an increase in precision (from 0.96 to 0.98) and recall (from 0.94 to 0.97), maintaining high AUC values of 0.97 in both cases, as shown in Tables 6.3 and 6.4. LSTM also demonstrated an improvement in AUC, increasing from 0.96 to 0.98, indicating its robustness and enhanced ability to handle feature selection, further emphasizing the strength of both models in managing complex datasets effectively.

Nonetheless, considering the resource-constrained miniature device in which the selected model will be deployed, factors such as computational efficiency, memory

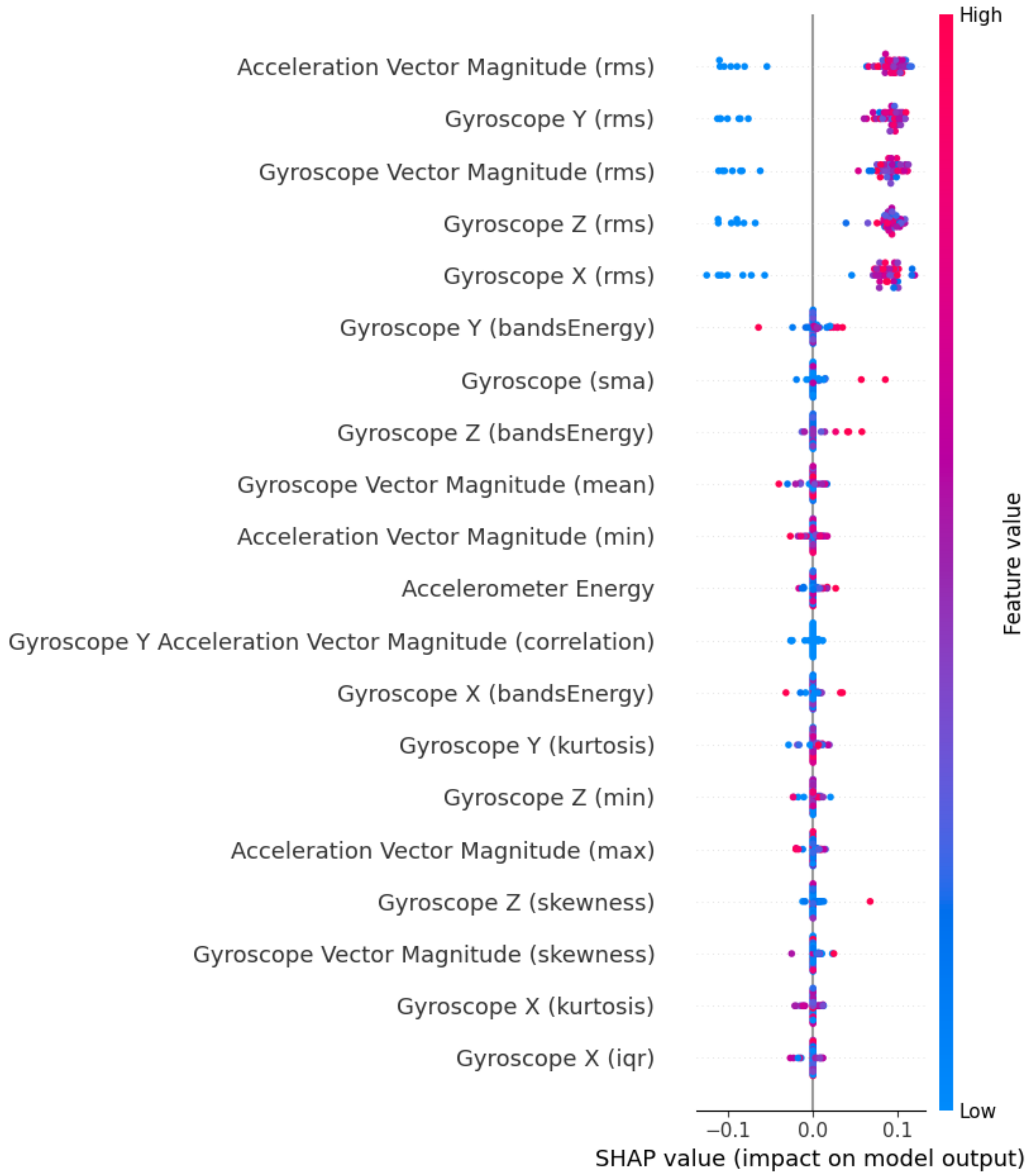


Figure 6.4: The feature impact on the XGBoost model output using SHAP.

usage, and inference time are paramount. LSTM, though highly accurate, is computationally expensive, requiring significant memory and processing power due to its recurrent nature, which involves storing and processing sequential data over multiple time steps [240]. This makes it less ideal for low-resource environments/devices, where lightweight and energy-efficient models are essential.

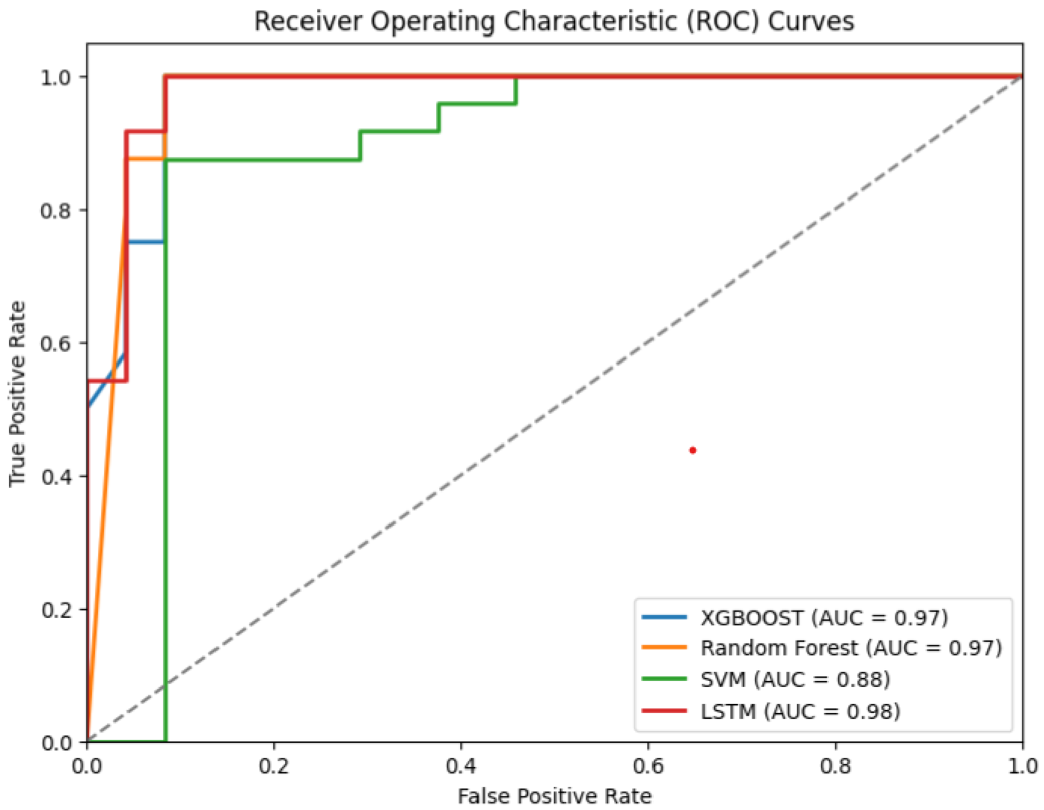
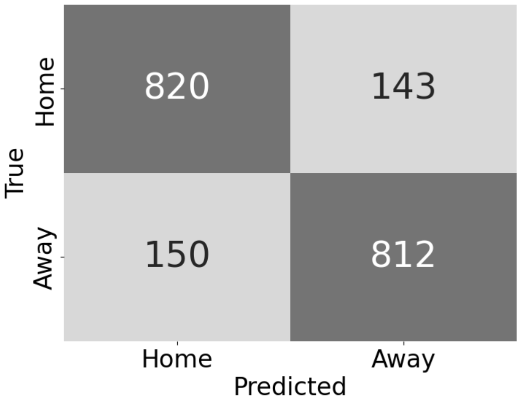


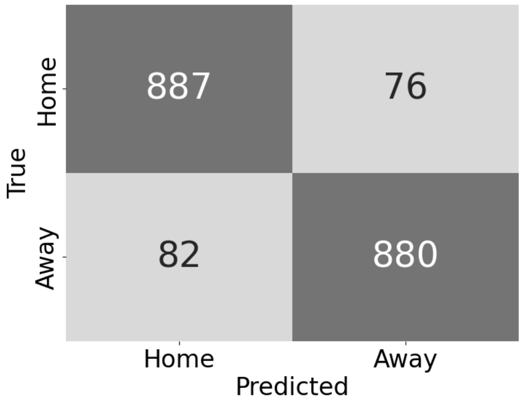
Figure 6.5: Results from AUC-ROC.

XGBoost, on the other hand, strikes a balance between high performance and efficiency. It employs gradient boosting, which is computationally faster than LSTM and more scalable in terms of memory usage. Moreover, XGBoost can be optimized through early stopping and parallelization, further enhancing its suitability for deployment in resource-constrained settings [227, 241]. XGBoost's ability to manage non-linear relationships without the same resource demands as LSTM gives it a clear advantage in environments with limited processing power and memory.

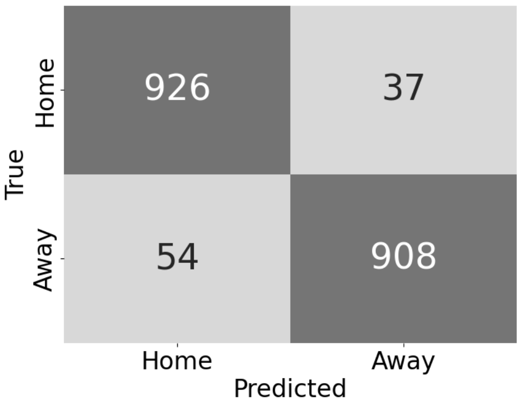
SVM lags behind in overall performance, indicating limited generalization of unseen data. This is likely due to their linear nature, which may not effectively capture the complexity of the dataset. Its performance is adequate but may not be ideal for large-scale or complex environments where high accuracy and recall are critical, as in this study. In contrast, despite promising results on the selected features, RF still falls slightly behind XGBoost in accuracy (0.93) and AUC (0.93),



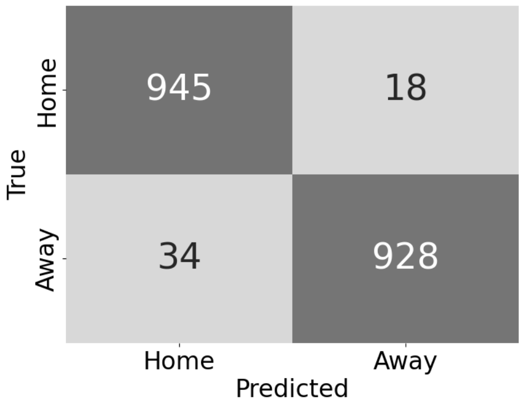
(a) Confusion matrix SVM model



(b) Confusion matrix for RF model



(c) Confusion matrix for XGBoost model



(d) Confusion matrix for LSTM model

Figure 6.6: Confusion matrix for all models using only selected features. Home: ”at home”; Away: ”walking away.”

possibly due to its lack of boosting, which limits its ability to reduce bias. However, it may still be viable in scenarios where computational constraints are strict but performance requirements are moderate.

It should be noted that all the models performed better on selected features than on the whole dataset, highlighting the importance of feature reduction in our work. Their performances are also demonstrated in Figure 6.6, with all models easily differentiating home activities from walking away from home, a key feature in GNSS activation. Figure 6.7 shows the F1-scores for different models on selected features against the whole dataset. LSTM (Figure 6.6d) performs best with minimal misclassifications (18 false positives, 34 false negatives), indicating superior accuracy in activity differentiation.

Considering the resource-constrained miniature device in which the selected model will be deployed, factors such as computational efficiency, memory usage, and inference time are of high importance. LSTM, while offering strong accuracy, requires considerable computational power and memory, as illustrated in Table 6.5. Table. 6.5 presents the comparison of models in terms of memory space, training, and inference times. This makes LSTM less practical for low-resource devices. XGBoost, in contrast, provides a balance between performance and efficiency, with lower computational and memory space demands compared to LSTM, making it more appropriate for resource-constrained environments.

In conclusion, the trade-offs between performance and resource efficiency make XGBoost the most suitable model for deployment in resource-limited environments. Its high accuracy and AUC scores, coupled with its computational efficiency, make it the ideal model to export to our low-cost resources device.

Table 6.5: Comparison of model space, training time, and inference time.

Model	**Space with selected features (MB)**	**Space with all features (MB)**	**Training time (ms)**	**Inference time (ms)**
LSTM	1.10	9.3	39711	5086
XGBoost	0.8	6.8	320.8	9.26
SVM	0.7	5.95	65.1	7.8
RF	0.6	5.1	877.6	43.25

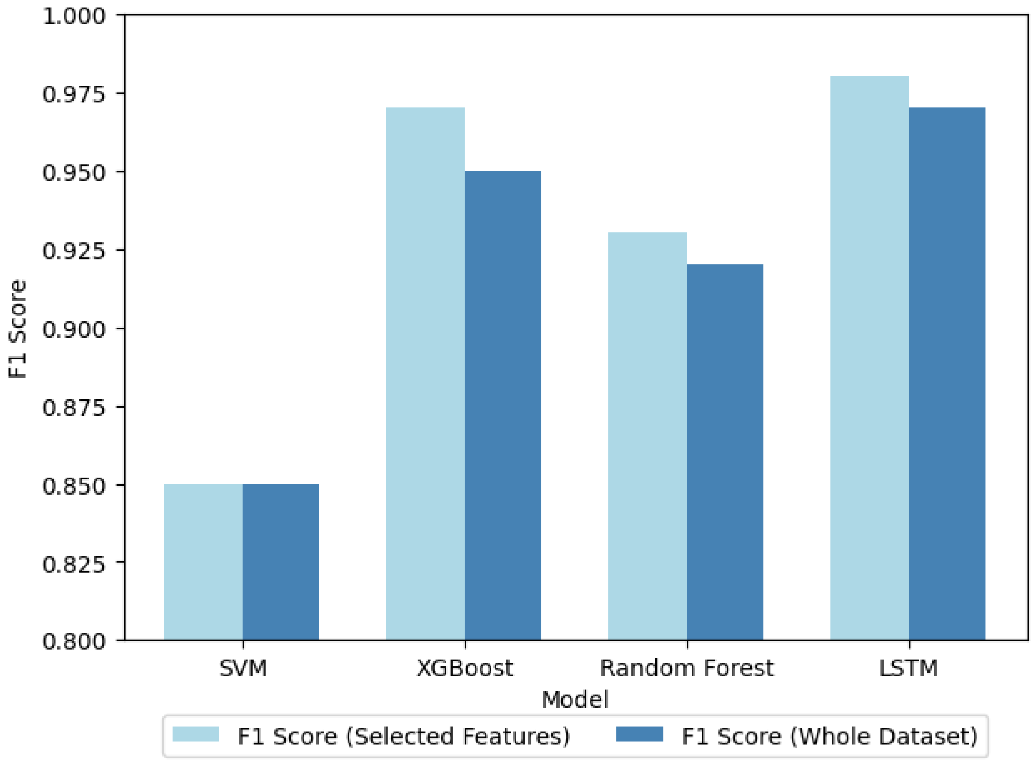


Figure 6.7: F1-scores for different models on selected features vs. the whole dataset.

6.3 GNSS activation tests

The goal of the experiments is to practically use our ML model embedded on the device to assist in distinguishing or reporting whether a user is around home or moving away from home, with the purpose of triggering GNSS activation or not.

In these experiments, we show that using just user motion/acceleration to activate the GNSS is not good enough, especially with human subjects. This work proposes a smarter and more efficient algorithm for GNSS activation by using ML to distinguish motion mode/activity by users around their homes from those moving away from their homes, as demonstrated in our experiments.

6.3.1 Experiments description

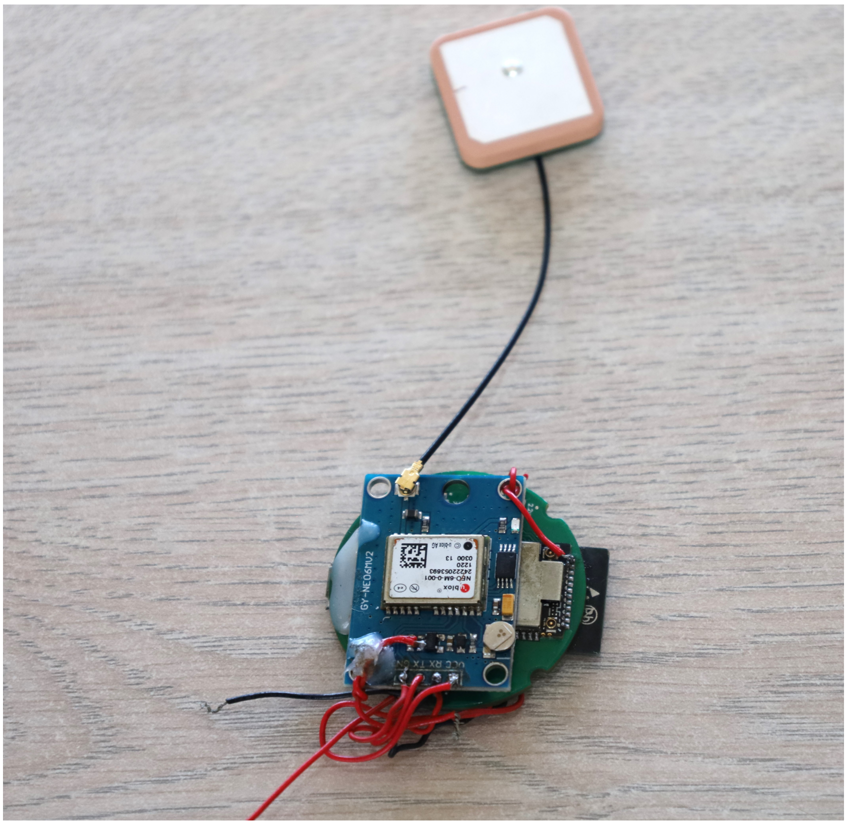
We conducted different experiments to assess the effectiveness of our developed method. This was specifically to evaluate the GNSS activation and the effect of user activity classification. To evaluate our GNSS activation method, we compared our method with a method we implemented inspired by work from the literature [196]. This system activates the GPS based on the user's mobility state, turning it on when the user is in motion and deactivating it once stationary for a configurable interval of 10 minutes. The following three experiments were used to evaluate our system:

- **Experiment one: Continuously walking at home**
  In this experiment, the user continuously walks (in motion) inside the house from one room to another and around the home for six minutes. The purpose of this experiment is to demonstrate that in our method, the GNSS is not activated only when you walk within and around the home, even though both activities involve walking. Hence, there is power saving compared to the user motion-based method, where the GNSS will continuously be active as the user's mobility state is constantly in an in-motion state. The expected result was that our method would yield zero GPS activations during these at-home movements, demonstrating the elimination of unnecessary power usage. We carefully monitored the classifier outputs: indeed, in this scenario, our model predominantly output class "0" (at home) for the windows, with only a few sporadic "1" predictions that were immediately disregarded by the smoothing logic. The power log should show a stable current draw of $\sim$55 mA for our method, versus a fluctuating current of $\sim$110 mA for the motion-based (the measured baseline current during motion was $\sim$0.10–0.12 A). This experiment addresses the examiner's point about demonstrating that acceleration alone is not a good trigger: even though the volunteer was constantly walking, our smarter algorithm recognized it as local movement and saved energy by not activating GNSS

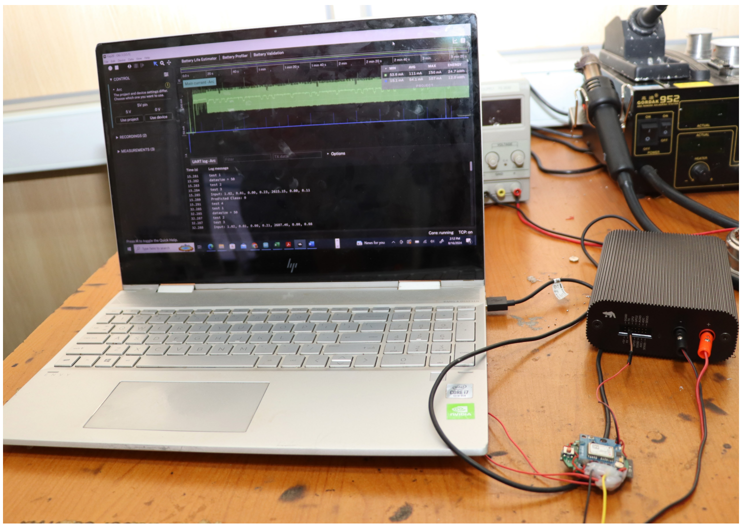
- **Experiment two: Everyday user activities at home**
  In this experiment, we conducted daily user activities within and around the home and as the user walked away from home to work. The activities included walking from one room to another, sitting, sleeping, standing, washing utensils, and finally, walking away from home. Each of these six activities lasted two minutes. The objective of this experiment is to show that our method does not mistake any home activities for walking away from home activities. Our

method should not misclassify any home activities as ‘away’ – i.e., during activities 1–5, GNSS should remain off – and it should correctly detect activity 6 as ‘walking away,’ activating GNSS promptly when the volunteer exits the yard. The baseline motion-based system, on the other hand, would behave nearly oppositely: it would turn on GNSS whenever the volunteer was moving (which is most of the time during activities 1 and 5, and certainly during the final walk) and possibly turn it off only during longer stationary periods (sitting, sleeping) if they exceeded 10 minutes (which they did not – only 2 minutes each, so the baseline likely never turned GPS off at all in this sequence). Thus, the baseline would keep GPS on through activities 1 and perhaps 5 and 6, leading to many unnecessary active minutes. In our results, we indeed observed that our ML model consistently output the ’at home” class for all segments 1–5, never erroneously triggering GNSS. When the volunteer began walking away (activity 6), the model confidently switched to “walking away” within $\sim$ 5-10 seconds, and the system enabled GNSS. Only at that point did the current jump to $\sim$ 140 mA. We thus confirmed that everyday domestic activities – even those involving walking or arm movements – were successfully recognized and filtered out by the model, avoiding false activations. This experiment provides evidence of the model’s specificity: normal home behaviors do not confuse it into thinking the user has left. The ability to incorporate multiple sensor features (not just step count) likely helped the classifier differentiate, for example, walking in small circles in a room (which has a different motion signature from a steady, forward walk out the gate). We justify our methodological choice of using an ML classifier here. Simple thresholds on acceleration cannot capture these subtleties, while the trained model successfully generalizes to various at-home contexts.

- **Experiment three: Walking at home against walking away**
  Walking (in motion) continuously inside the house from one room to another, around the home for 6 minutes, and after walking away from home also for 6 minutes. This experiment aims to demonstrate that the GNSS is only activated when the user ”walks away” from home. It also shows that our model easily distinguishes walking around the home from walking away from



(**a**) PCB



(**b**) Experimental setup.

Figure 6.8: Designed embedded system.

home, aligning power use with the user's context. Even with continuous walking at home, our model held off on GPS until the departure occurred. It also highlights the smooth handover: the model didn't hesitate or lag in triggering GPS once the user transitioned to leaving; thanks to the 5 s window and consecutive prediction check, we had GNSS on within $\sim$ 15 s of the actual exit, which is acceptable for our application (and could be tuned for even faster response if needed by reducing the window or consecutive count).

Throughout these experiments, we logged the system's classification outputs, the GNSS activation status over time, and the current draw using the Otii Arc Pro device for precise energy measurement. The Otii was connected in line with the device's battery to record real-time current consumption at a 1000 Hz sampling rate. This provided us with detailed power profiles for both our method and the motion-based method under identical activity conditions. For example, in Experiment 1, the Otii logs showed that our method drew a stable approximately 0.055 A with only minor fluctuations (microcontroller activity) and 0 A from the GPS. In contrast, the motion-based method continuously drew approximately 0.11–0.12 A (GPS on plus MCU). We utilized Otii's battery life estimation feature to extrapolate these findings: with a 4000 mAh battery, the motion-based method would deplete in roughly 1.5 days, while our method would last over 3 days under the same usage pattern – a more than 40% improvement in battery life, as noted earlier. These quantitative results reinforce the value of the methodological choices (5 s window, feature selection, XGBoost model); they achieve substantial energy savings (over 40% in our tests) while maintaining accurate detection of the critical event (walking away).

6.3.2 Model integration and hardware setup

6.3.2.1 Model deployment and data collection

LSTM was the best model but could not be installed in our embedded system because of the memory and computation power limitations (Table 6.5) even after feature reduction. Therefore, the second-best model, XGBoost, was selected and used in experiments. The selected XGBoost model was converted to a lightweight model and deployed on our designed embedded system using Eloquent ML libraries, which port the model to C++ code that runs on the ESP32 microcontroller.

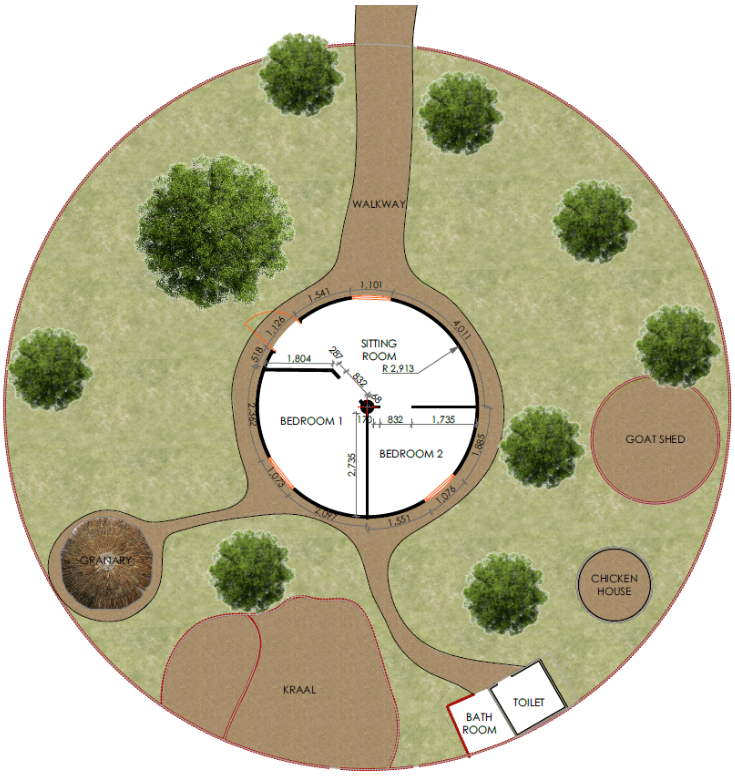


Figure 6.9: House plan simulated to conduct the three experiments.

For this experiment, an embedded system on a custom-designed Printed Circuit Board (PCB) was designed and assembled, as shown in Figure 6.8a. The PCB integrates an ESP32 microcontroller (with a sleep current of less than 5μ A, ideal for battery-powered wearables), a 6-axis IMU (MPU6050), and a NEO6 GPS module for positioning. The GPS module's compact architecture and power efficiency make it suitable for battery-powered devices with cost and space constraints. It also comes with a small battery for hot-start and built-in EEPROM to save configuration settings when turned off. The PCB also supports lithium-ion battery charging via an onboard USB connector, enabling easy programming. This custom design allowed for system miniaturization, making it suitable to be worn or carried by the user.

We also used the Otii Arc Pro, a high-precision energy consumption analysis tool, to measure the power consumption of our system [242]. Otii Arc Pro and our embedded system communicated via USART serial interface, with a baud rate of 115200, to capture logs for analysis, as shown in Figure 6.8b.

6.3.2.2 Experiment execution

We conducted our experiments on an open field at Makerere University football ground, aiming to replicate a rural, resource-constrained environment characterized by scattered, poor, inadequate, semi-structured buildings and minimal GNSS signal interference. To simulate the home setup accurately, we recreated the house plan depicted in Figure 6.9 by using cones to demarcate key sections and boundaries. Using cones allowed us to represent important areas of the house in an open environment, thus providing a realistic yet controlled setting. During data collection, the volunteer mounted the embedded system on the wrist and performed the experiments as defined in section 6.3.1.

We automatically record the raw inputs of the accelerometer and gyroscope at a sampling rate of 10 HZ. These are then windowed using a window size of 5 seconds, and each of the top 10 selected features is computed across each window. These are then sent into the ported model to obtain a prediction of whether the person with the device is ”walking away” or ”at home.”

6.3.2.3 GNSS activation

Our system only activates the GNSS when the user activity is presumed to be walking away based on a sequence of predictions as illustrated in Figure 6.10. Our system is designed to determine whether a user is around the home (prediction class 0) or walking away (predicted class 1). Depending on the output, the counter is updated at the end of every prediction. After six predictions, the system evaluates the results; if prediction class 1 outnumbers class 0, the system activates GNSS and notifies the caretaker. The decision to use six predictions aims to balance safety with system efficiency. 30 seconds is a good enough time to respond, considering this system is designed to monitor elderly people; their safety is paramount, and timely responsiveness is essential. Evaluating six predictions ensures quick and reliable action while avoiding unnecessary GNSS activation. A seventh prediction determines the final action in cases of an even split. If this prediction indicates class 1, GNSS is activated, and a notification is sent. This approach ensures GNSS activation only when there’s a clear indication of the user leaving home, minimizing unnecessary activation and alerts.

6.3.3 Justification of Methodological Choices

We ensured that each aspect of the ML-based system was chosen with resource constraints and literature guidance in mind. The wrist-worn placement was selected because a wrist device is practical for continuous use by an elderly person (e.g., as a bracelet) and still provides a strong motion signal for walking detection. Notably, our PDR tests indicated that wrist (hand) placement pairs well with algorithms like pitch-based detection; here, we rely on ML to automatically handle the motion patterns. The 10 Hz sampling rate and 5 s window are supported by prior HAR research as a reasonable compromise for low-power devices. The feature-based ML approach is far more interpretable and tunable than a raw-sensor end-to-end model. We can easily adjust thresholds or add logic (as we did to filter outliers) to refine the system. XGBoost, in particular, proved to be a good fit because it achieved near-state-of-the-art accuracy in distinguishing activities while being efficient enough to run on an MCU. This aligns with other works that have deployed boosting algorithms on embedded platforms for real-time classification. Additionally, by limiting features to 10 and using fixed-point arithmetic in the embedded inference, we significantly reduced computation, an important factor given the energy cost of computing in battery-operated devices. Each inference on the ESP32 consumed only a few millijoules, which is negligible compared to the energy required to power the GPS for even one second.

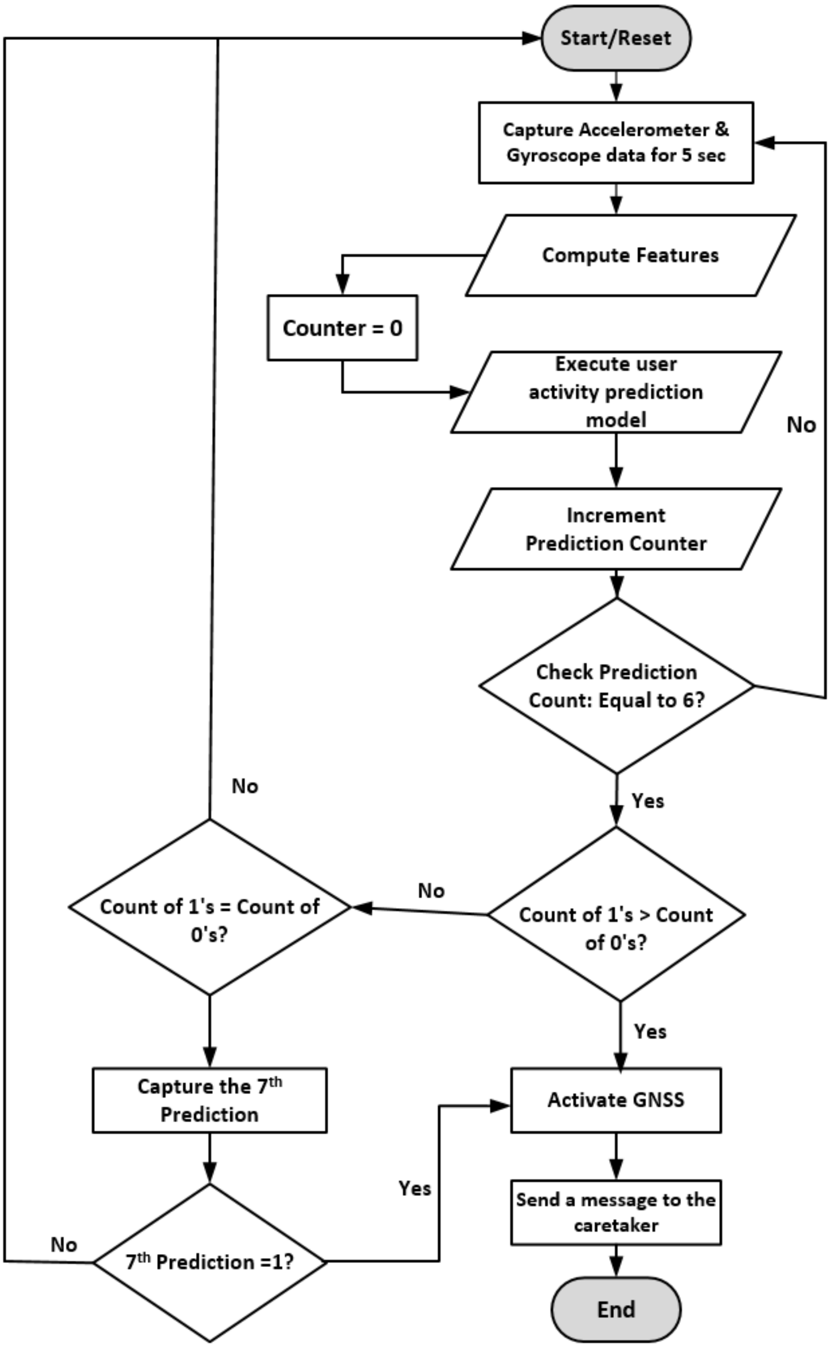


Figure 6.10: Flowchart for our user activity-based GNSS activation system.

In summary, our methodological decisions, from data segmentation to model selection, were driven by the twin goals of accuracy (avoiding missed detections or false alarms of walking away) and energy efficiency (minimizing overhead on a constrained device), consistent with the challenges identified for resource-constrained remote monitoring.

6.3.4 Results and Discussion

The following represents the results and analysis of the three experiments that were conducted.

6.3.4.1 Experiment one: Continuously walking at home

In experiment one, the user walked continuously for six minutes, moving between rooms and around the home. This setup aimed to evaluate the classifier's performance and power consumption during sustained user movement.

Figure 6.11 presents the results of both the classification model and the power consumption analysis for this activity. The classifier's output and power usage for our proposed method are compared with the acceleration-based model, highlighting the performance differences in terms of GNSS activation and energy efficiency.

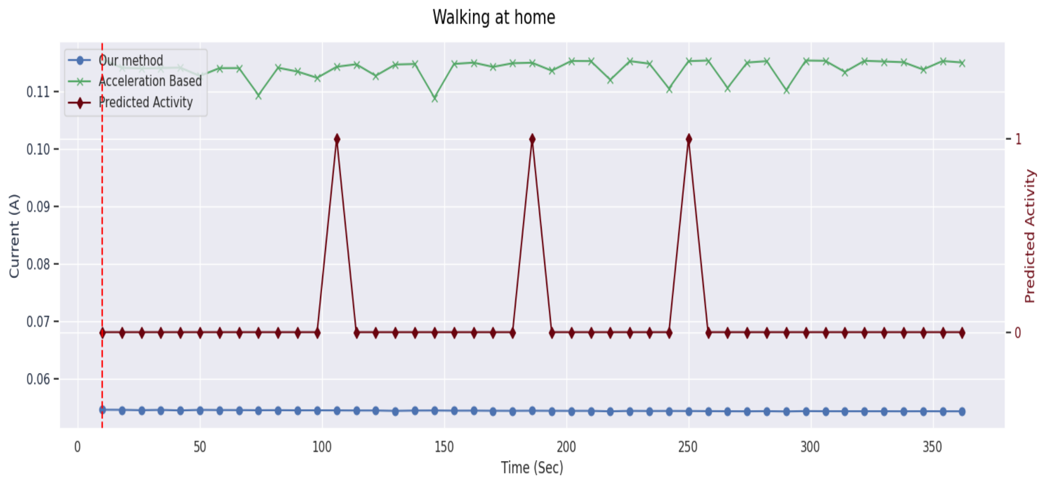
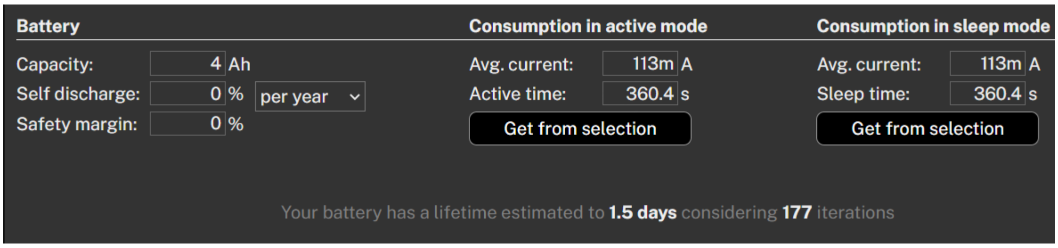
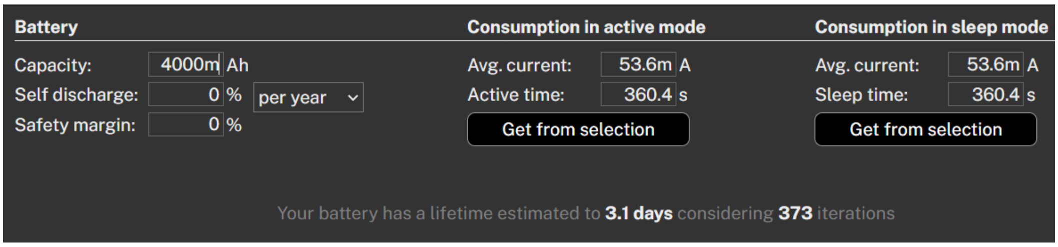


Figure 6.11: Power consumption of the proposed model against motion-based method as the user continuously moves around at home. 0: ”at home”; 1: ”walking away.”



(a) Battery life estimation with acceleration-based method.



(b) Battery life estimation with our method.

Figure 6.12: Battery life estimation for our method against the motion-based during experiment one.

The classification results demonstrate that our method accurately identified most of the ”walking at home” activities as ”at home,” ensuring that GNSS was not activated during the six-minute continuous walk. Although there were three instances where the activity was misclassified as ”walking away,” the final decision logic of our system (detailed in Figure 6.10) was designed to disregard these outliers, preventing unnecessary GNSS activation.

In terms of GNSS activation and power consumption, our method maintained a much lower and stable current draw, around 0.055 A, compared to the acceleration-based method, which exhibited higher consumption, fluctuating between 0.10 A and 0.12 A throughout the experiment. It should be noted that in resource-constrained rural environments, people spend most of their time outdoors around their houses, so it is unnecessary to activate the GNSS so frequently to monitor them. Results show that our model does not classify walking at home as walking away, in contrast to a basic walk detector. This helps to avoid enabling GNSS when the user is around the same location, saving some energy.

For example, with a 4000 mAh battery, the acceleration-based model would last approximately 1.5 days, as shown in Figure 6.12 from the Otii battery estimator.

Our method extends the battery life to 3.1 days, resulting in over 40% battery savings. This demonstrates the superior efficiency of our model and highlights its suitability for continuous activity monitoring around the home, particularly in resource-constrained environments.

6.3.4.2 **Experiment two: Everyday user activities at home**

Figure 6.13 presents the analysis of data collected during experiment two, where the user walked continuously for 6 minutes from one room to another and around the home, followed by an additional 6 minutes of walking away from the home. The figure illustrates both the classification results and power consumption analysis for our proposed model against an acceleration-based model.

Our model correctly classified most activities within the home, ensuring that the GNSS was never activated during these activities. The classification results show that activities such as sitting, standing, sleeping, and washing utensils were correctly predicted as ”at home” without unnecessary GNSS activation.

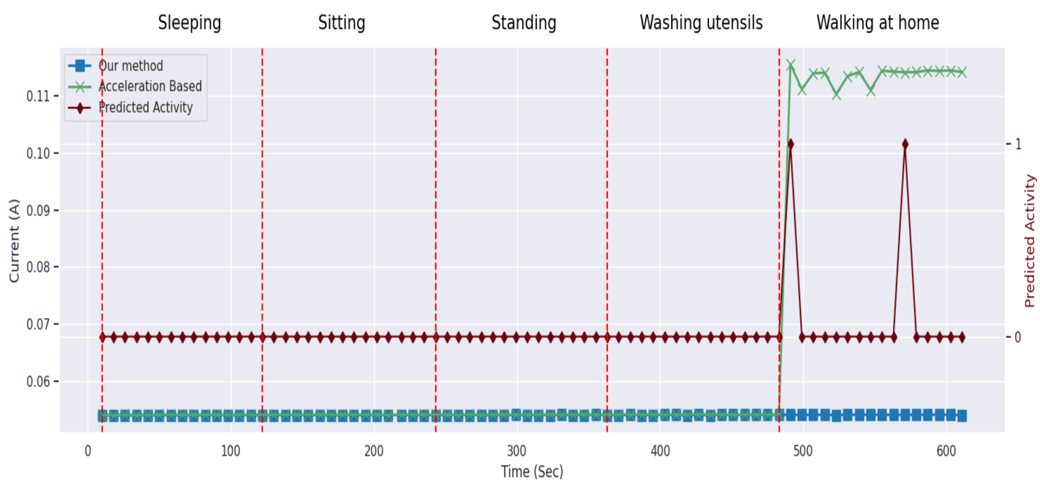


Figure 6.13: Performance of our model vs. the motion-based method during everyday user activities within and around the home during experiment 2. 0: ”at home”; 1: ”walking away.”

Regarding power consumption, both models showed minimal current usage during stationary activities like sitting, standing, sleeping, and washing utensils, with consumption at approximately 0.055 A. However, during the ”walking at home” activity, the acceleration-based method's power consumption increased significantly, with current spikes ranging between 0.1 A and 0.12 A, due to unnecessary GNSS activation triggered by motion detection. In contrast, our method maintained a stable low consumption of around 0.055 A throughout, showcasing better power efficiency. Despite some false classifications of "walking away" during the "walking at home" activity, our method was robust enough to avoid GNSS activation, as it effectively ignored these outliers based on the decision-making flow outlined in Figure 6.10. It should be noted that the red vertical delimiters represent the activity ground truth.

6.3.4.3 **Experiment three: Walking at home vs. walking away**

Figure 6.14 presents the analysis of data collected during experiment three, where the user walked continuously from one room to another and around the home, followed by walking away from the home. The figure illustrates both the classification results and power consumption analysis for our proposed and the acceleration-based method. The red vertical delimiters represent the activity ground truth, providing a reference for model performance.

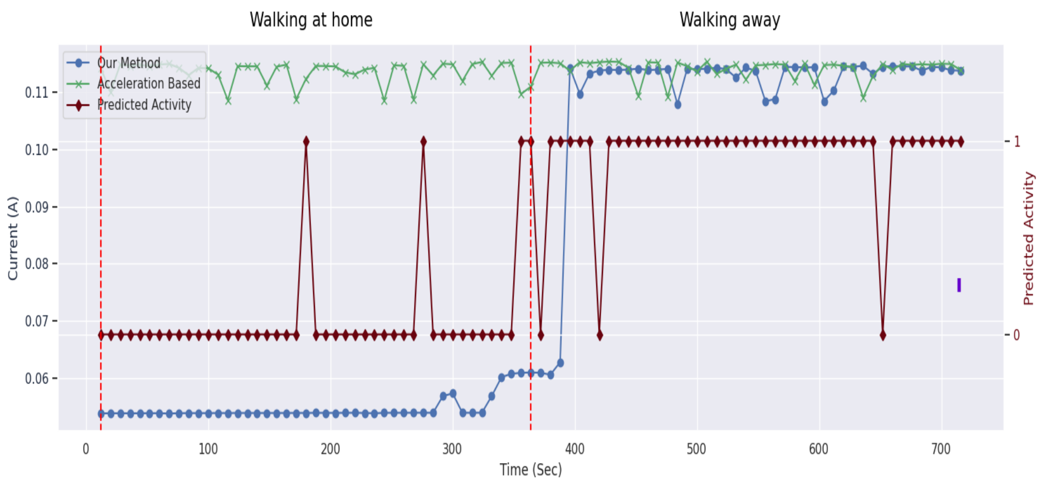


Figure 6.14: Power consumption of the motion-based method against our model as the user walks around home and away from home during experiment 3. 0: "at home"; 1: "walking away."

Our model effectively classified most home activities without activating GNSS during the continuous walk around the home. Unlike the acceleration-based model, which kept GNSS active and showed increased power consumption (0.1 A to 0.12 A), our model consistently maintained a low consumption of around 0.055 A and only activated GNSS when the user walked away.

The results, even though on short-duration activities, demonstrate that our model offers significant power efficiency advantages over the acceleration-based approach by consuming minimal power when the user remains at home and only increasing consumption when necessary. Moreover, accurate activity predictions ensured energy use aligned with real-time user actions, making our model a more sustainable solution for continuous monitoring applications, especially for tracking elderly individuals with dementia in resource-constrained environments.

The experiments that were conducted provided power consumption data based on short-duration activities, so to better illustrate real-world savings, we extrapolated these findings to a realistic daily scenario typical of elderly individuals in rural, resource-constrained settings. Given that elderly people generally spend most of their day (approximately 10-12 hours) at home or within close proximity performing routine, low-intensity activities, and roughly 1 hour daily actively walking away from home for tasks like fetching water or visiting nearby neighbors or trading centers, our GNSS activation method, which specifically detects the ”walking away” activity class, can significantly reduce unnecessary activations.

Using our experimental data indicating a 40% reduction in power consumption compared to conventional activity-based GNSS activation methods, we estimate that with a standard 4000 mAh battery, the frequency of required recharging could reduce from approximately once every two days (typical for motion-based methods) to about once every four to five days. This extended battery life significantly reduces the burden on elderly users or their caregivers, who often must travel considerable distances—typically several kilometers—to trading centers for battery recharging. Thus, our approach not only extends battery life but substantially improves the practicality and sustainability of remote monitoring solutions in resource-constrained environments.

To provide a clear comparative overview of the results and better illustrate the performance of our proposed model relative to existing methods, Table 6.6 summarizes the GNSS activation frequencies, estimated battery life, and energy savings across all conducted experiments.

Table 6.6: Summary and Comparison of Experimental Results

Experiment	**Method**	**GNSS Activation Frequency**	**Battery Life (4000 mAh battery)**	**Battery Saving (%)**
Continuously walking at home (6 min)	Acceleration-based	Continuous activation	1.5 days	Baseline (0%)
	Our method	No activation	**3.1 days**	>**40%**
Everyday activities (12 min total)	Acceleration-based	Frequent activation	1.8 days	Baseline (0%)
	Our method	Minimal activation (only when leaving home)	**3.2 days**	>**40%**
Walking at home vs. walking away (12 min)	Acceleration-based	Activated during both	1.6 days	Baseline (0%)
	Our method	Activated only when ”walking away”	**3.0 days**	>**40%**

From Table 6.6, it is clear that our method consistently provides over 40% energy savings compared to generic motion-based GNSS activation methods. These results support our hypothesis that explicitly detecting ”walking away” significantly reduces unnecessary GNSS activations and improves battery performance, aligning with the specific needs of remote elderly monitoring in resource-constrained settings.

6.3.5 Discussion

Our model has effectively demonstrated its ability to differentiate between user activities ”at home” and ”walking away,” thereby minimizing unnecessary GNSS activation. This approach extends battery life by more than 40% when the user remains around the home. The model has also shown reliability in accurately detecting when a user walks away and activating the GNSS with minimal errors. While a small number of ”walking away” activities were misclassified as ”at home,” this did not affect the GNSS activation decision. It is evident that user motion alone is insufficient to justify GNSS activation, as the movement does not always indicate danger or a need for caretaker intervention. Activating GNSS solely based on motion would lead to unnecessary energy consumption and reduced battery life, which is especially important in resource-constrained areas with limited access to electricity.

6.4 Conclusion

Chapter 6 presented a novel ML-driven GNSS activation method tailored to resource-constrained environments for detecting the activity of walking away from home to another location with the purpose of triggering (activating or deactivating) the GNSS.

This chapter has presented the development and implementation of an ML method for detecting the activity of walking away from home to another location with the purpose of triggering (activating or deactivating) the GNSS. The core idea of our method is detecting the activity of ”walking away” from home to another location, which is sufficient for resource-constrained environments. This approach eliminates the need for beacons, avoids assumptions about varying signal strengths indoors and outdoors, is superior to basic acceleration signal thresholding, and is simpler than comprehensive human activity recognition, as it focuses solely on distinguishing between being at home and walking away. This approach harnessed the power of ML to discern between user motion modes at home and when moving to a different location. The results from multiple experiments show that our method can extend battery life by over 40% compared to motion-based systems, as demonstrated using the current draw, making it highly efficient and practical for monitoring elderly individuals with dementia in resource-constrained environments.

Our proposed ML-driven GNSS activation method accurately differentiated between home-based and walking-away-from-home activities. The effectiveness with which this is done effectively minimized unnecessary GNSS activations. It also ensured reliable and timely alerts when users moved away from home, reducing false alarms and optimizing performance for continuous monitoring systems. It provides a more sustainable and practical solution for real-world applications.

CHAPTER

7

Conclusions

7.1 Conclusions

This chapter closes this work. Section 7.1.1 presents the main contributions of this thesis, and Section 7.1.2 presents the key learnings and main conclusions reached during this thesis. Subsequently, Section 7.2 outlines potential directions for future work in resource-constrained environments. Finally, Section 7.3 lists the articles that have been published in relation to the results of this thesis.

7.1.1 Summary of Main Contributions

The research presented in this thesis aimed to address the specific challenges associated with remote pedestrian localization in resource-constrained environments, focusing on enhancing energy efficiency while maintaining reliable performance. The main contributions can be summarized as follows:

- **Characterization of Resource-Constrained Environments**: The study clearly defines and distinguishes resource-constrained environments from resource-constrained devices by highlighting critical operational challenges. Chapter 2 established that many resource-constrained regions, particularly in low- and middle-income countries, lack stable electricity, continuous Internet connectivity, reliable cellular networks, and advanced infrastructure. These limitations significantly restrict the effectiveness of existing localization systems, underscoring the need for specifically tailored approaches. This characterization provides an essential foundation for evaluating technological suitability within such challenging contexts.

- **Systematic review of existing remote pedestrian localization systems**: A systematic literature review (Chapter 3) was conducted to assess existing outdoor pedestrian localization systems, with a focus on their suitability in resource-constrained environments. The review revealed that most existing positioning technologies assume ready access to infrastructure, such as Wi-Fi, cellular signals, or continuous power. These assumptions limit the applicability of existing systems in low-resource settings. Notably, GNSS emerged as the most suitable technology for accurate, long-range, infrastructure-free outdoor localization despite its inherent power demands. This analysis provided a comparative baseline, motivating subsequent optimization efforts within this research.

- **Proposed two resource-optimized solutions for GNSS activation**: Two innovative GNSS activation strategies (Chapters 5 and 6) were developed and empirically validated to enhance energy efficiency in wearable IoT devices:

  – *Position-Based GNSS Activation using PDR (Chapter 5)*: This is a position-based GNSS activation method that uses a PDR system as the main input source. The aim was to design a GNSS activation method that is better than the usual activity-based methods for pedestrians (commonly acceleration-based) and cheaper than common position-based methods requiring beacons. The proposed method was based on defining a geofence around the user's home such that the GNSS is only turned on when the user's position is estimated to be outside the geofence (safe zone). This method effectively minimized power consumption and demonstrated feasibility for environments with limited resources like continuous power or communication infrastructure. Experimental evaluations showed that this proposed GNSS activation method achieves higher power optimization (by more than 90% in and outside the safe zone) than acceleration-based ones without installing any beacon, making it better for resource-constrained environments.

– *ML-Driven User Activity-Based GNSS Activation (Chapter 6)*: This is an ML-based method for detecting the activity of walking away from home to another location with the purpose of triggering (activating or deactivating) the GNSS that was introduced. The core idea of this proposal was detecting the activity of "walking away" from home. This approach is sufficient for resource-constrained environments, as it eliminates the need for beacons, avoids assumptions about varying signal strengths indoors and outdoors, is better than just a basic acceleration signal thresholding, and is simpler than human activity recognition since it does not need to classify different daily user activities. It is also not affected by accumulated errors resulting from using the PDR system for positioning. This approach harnesses the power of machine learning to discern between user motion modes at home and when moving to a different location. The experimental validation showed a substantial improvement in power efficiency, extending the battery life by more than 40% compared to acceleration-based systems.

These contributions demonstrate that GNSS-based localization can be more feasible in low-resource contexts through careful system design and reduced reliance on continuously active positioning. Additionally, the methods introduced offer distinct trade-offs that expand implementation choices based on local infrastructure and user needs.

7.1.2 Discussion and Reflection on Findings

The research presented in this thesis aims to enable effective and energy-efficient remote localization of elderly individuals in resource-constrained environments. This objective is motivated by the growing needs of aging populations in regions with limited infrastructure, where traditional monitoring solutions are often unfeasible.

For example, by 2050, nearly two-thirds of the world's elderly population is expected to reside in low- and middle-income countries, many of which lack reliable electricity and communication services. In such settings, elderly individuals like Jolly – a 78-year-old resident of a rural village with no stable power or cellular network – face significant challenges in remaining safe and connected to their caregivers. The findings of this work demonstrate that it is possible to bridge this gap through careful system design and innovative GNSS activation techniques, enabling reliable outdoor tracking with minimal power usage and infrastructure dependence. This chapter discusses the key research results and reflects on how they address the initial goals and real-world needs, highlighting implications for elderly care, energy-efficient localization, and scalable deployment in low-resource settings.

- **Reconciling Energy Constraints with Rural Lifestyles**
  A primary challenge in remote localization for resource-constrained areas is energy efficiency. Devices must operate for extended periods on battery power because regular recharging is often difficult in off-grid communities. The experimental results confirm that the developed position-based GNSS activation method effectively mitigates this challenge. By using a geofence safe zone around the user's home and leveraging a PDR mechanism, the system drastically reduces unnecessary GNSS activations. In practice, the GNSS module stays off during routine indoor or yard activities and only turns on when the person moves beyond their predefined "safe" boundary. This approach yielded substantial power savings, achieving over a 90% reduction in GNSS energy consumption compared to a conventional continuous or motion-triggered tracking method. Such a dramatic improvement means a wearable tracker can run for much longer on the same battery charge, an outcome especially crucial in communities where recharging might require walking miles to a charging station or waiting for an unreliable electricity supply. The geo-fencing strategy aligns well with typical rural elderly lifestyles, as many elders tend to engage in short, repetitive activities near their homes, such as tending a garden or visiting a neighbor. The system capitalizes on this pattern by minimizing power draw during these safe activities while still reliably detecting when the person walks away from the safe zone. In summary,

the position-based method reconciles the strict energy constraints of remote villages with the user's lifestyle, ensuring that battery life is preserved without compromising safety.

- **Embracing Family-Based Care and Autonomy**
  Another key aspect of the findings is how the solutions integrate into the family-based caregiving model common in low-resource settings. In many rural communities, professional healthcare support is scarce, and elderly individuals often rely on distant family members for oversight and decision-making. Traditional monitoring systems often assume continuous connectivity or constant caregiver attention, which is unrealistic when family members live far away and are limited to periodic monitoring. The proposed machine learning- driven GNSS activation method addresses this gap by effectively distinguishing between normal daily behavior and potentially risky situations that warrant an alert. By analyzing inertial sensor data, the system's ML model detects the specific activity of "walking away from home" and triggers GNSS only for those events. This means that everyday movements, such as walking within the house or yard, are filtered out, and only significant departures activate location tracking. The benefit of this intelligent filtering is twofold: it respects the autonomy of the elderly user, and it reduces false alarms for caregivers. Elderly individuals in these communities often highly value their independence and adhere to cultural norms that encourage them to stay active around their homesteads. The ML-driven approach supports this by not needlessly interfering during normal routines, thereby respecting the older person's dignity and freedom. At the same time, when the "walk-away from home" activity class is detected, the system can promptly alert family members. This selective, context-aware monitoring aligns with family caregiving practices – relatives are notified only when genuinely necessary, allowing them to respond to genuine signs of trouble without having to monitor data constantly. Ultimately, the findings demonstrate that technology can be integrated into existing social structures, enabling families to care for their elders remotely without compromising the elders' sense of independence. This balance between safety and autonomy is a critical social and ethical

consideration, and the success of the ML-based method in achieving it is a notable outcome of the research.

- **Reducing User Intervention through Context-Aware Design**
The technical design of the proposed localization solutions reflects a conscious effort to minimize user and caregiver burden, which was a significant consideration from the outset. Many elderly end-users and their caregivers in rural areas have limited digital literacy, and any solution requiring complex setup, frequent user interaction, or additional infrastructure would likely fail in practice. The research findings confirmed that both geofence-based and ML-based methods can operate autonomously, without requiring active input from the user or caregiver, in day-to-day use. The wearable device leverages onboard inertial sensors, including accelerometers and gyroscopes, along with embedded intelligence, to make decisions internally. This eliminates the need for the user to manually toggle modes or for a caregiver to constantly calibrate the system. This context-aware autonomy was demonstrated in the experiments: once configured with the home zone or trained on the user's activity pattern, the device autonomously managed localization triggers. Importantly, neither approach relies on external infrastructure, such as Wi-Fi or Bluetooth beacons, which are often unavailable in the target environments. By leveraging low-cost, built-in sensors and on-device processing, the system eliminates the need for additional hardware installations and technical maintenance. This significantly reduces the burden on caregivers, who might otherwise need to handle complex technology or perform frequent device maintenance. In practical terms, a caregiver in Jolly's village, who may lack technical expertise, would not have to do more than ensure the device is charged; the intelligent wearable takes care of the rest. This ease of use and low requirement for human intervention make the solution scalable and realistic for low-resource environments, as it can be deployed to many users without a specialized support network. The findings highlight that thoughtful, context-aware design can overcome the usability barriers that have hindered the adoption of remote monitoring technology within disadvantaged populations.

- **Harmonizing Localization with Caregiving Practices**
  Crucially, the developed localization techniques were shown to harmonize with existing caregiving practices and constraints in low-resourced environments. Family members caring for an elder at a distance often face uncertainty and anxiety, as regular communication can be difficult, and there is no easy way to know if an emergency arises. The proposed system bridges this gap by providing a form of remote situational awareness that fits into the family's routine. Because the GNSS is activated only for meaningful events (leaving the safe zone or walking away from home), the system can be configured to send timely notifications to designated family members or community health workers only when intervention is likely needed. This event-driven notification model was designed to work under the limited connectivity typical of these environments. Instead of requiring a continuous high-bandwidth link, a simple SMS or low-frequency update can be sufficient to alert caregivers when, for instance, an elderly person has left their home and may be confused. The findings indicate that such selective tracking is effective in practice: the device can successfully capture critical moments and relay an alert without requiring continuous network coverage or professional monitoring. This means the solution can fit into family caregiving patterns where a neighbor or relative checks in when alerted, rather than necessitating round-the-clock supervision by healthcare staff. It also preserves a sense of normalcy; the elder is not under obvious surveillance during their daily life, yet their family can be quickly informed of potential danger. In Jolly's case, for example, if she were to move beyond her familiar paths, the system could immediately notify her children in the city. They could then coordinate help (such as asking a nearby neighbor to find Jolly), a process far more efficient and reassuring than the current situation of infrequent phone calls and delayed information. By seamlessly integrating with how families actually provide care across distances, the localization system demonstrates a broader real-world impact: It offers a culturally appropriate, financially viable, and technically feasible tool to improve safety for the elderly. In essence, it empowers dispersed families to care for their loved ones proactively, enhancing traditional caregiving with timely, automated support.

- **Ethical and Societal Considerations**
  While the technical outcomes are promising, it is essential to consider the ethical and societal implications of deploying such a localization system. One consideration is privacy: tracking an individual's movements can be sensitive, and the system must ensure that data is handled securely and only shared with authorized caregivers. Fortunately, the approaches taken in this work inherently limit privacy intrusion by avoiding continuous surveillance. Location data is only generated and transmitted when a notable event occurs (e.g., exiting the safe zone), rather than providing a constant feed of the person's whereabouts. This event-based monitoring respects the individual's privacy and autonomy, using technology as a safety net rather than an invasive tracker. Still, implementing these solutions will require informed consent and transparency with elderly users and their families. Users like Jolly should understand how the device works and agree to its use, which involves striking a balance between their personal freedom and the added safety. A culturally sensitive introduction of the technology is crucial so that it is perceived as a tool of empowerment rather than an imposition. Additionally, data security measures must be in place to prevent any misuse of the sensitive information that is collected. On the societal level, the system carries the promise of reducing caregiver stress and healthcare burdens. Studies in remote care have noted that technology can make caregiving more efficient, safe, and less stressful for families. By providing peace of mind and quicker response in emergencies, the solution can improve the quality of life not only for the elderly themselves but also for their relatives who gain confidence that help can reach their loved ones when needed. Overall, these ethical reflections emphasize that technology alone is insufficient; it is how technology is deployed within the community, with respect for users' rights and local norms, that ultimately determines its success and acceptance.

The outcomes of this research confirm that it is feasible to perform remote pedestrian localization for elderly individuals under the severe power and infrastructure constraints that exist in rural, resource-constrained environments. By employing two complementary GNSS optimization strategies, the work achieved substantial power savings, with up to 90% in one approach and approximately 50% in the other, while maintaining accurate and reliable tracking performance. Notably, this was achieved without the need for new infrastructure or extensive user involvement, making the solution practical for scalable deployment in low-resource communities. The initial motivation to enable an elderly person like Jolly to be safely monitored remotely has been effectively addressed. If implemented, such a system would allow vulnerable seniors to age in place more safely, knowing that straying beyond safe boundaries will trigger assistance. Families, on the other hand, would be relieved of some of the anxiety and logistical burden, as they could trust the system to alert them to genuine concerns and thereby coordinate care more effectively. The broader implication is that energy-efficient localization technology can help fill an important gap in healthcare in under-resourced areas, thereby extending the reach of caregivers and healthcare services to remote locations. By tailoring the design to real-world conditions (including unreliable power, irregular network access, and cultural expectations of independence), this work bridges the gap between rural realities and modern remote monitoring solutions. In doing so, it provides a template for sustainable and scalable remote monitoring that acknowledges social and ethical nuances while remaining technically grounded in innovation. The findings and lessons from this research contribute to the ongoing efforts to make ubiquitous sensing and IoT-based care a reality for all communities, regardless of their resource limitations. Ultimately, enabling efficient remote pedestrian localization in resource-constrained environments is a significant step toward ensuring that older adults can live safely and with dignity in their own communities, supported by technology that truly meets their needs. Each insight gained from power optimization to user-centric design reinforces the central conclusion that with ingenuity and empathy, advanced localization systems can be adapted to empower some of society's most vulnerable members and deliver a tangible impact in the real world.

7.2 Future Research Work

While this thesis achieved its key goals, it also opened avenues for further investigation. One area to explore is the use of more advanced machine learning models (such as neural networks) to predict user movement patterns; for example, learning a user's daily routine to anticipate when they typically go out, thereby optimizing GNSS activation schedules even more. Another area is improving the PDR accuracy under various conditions: our work used two PDR implementations and highlighted differences; future work could integrate adaptive algorithms that switch or calibrate PDR methods based on context (e.g., recognizing if the device is in hand vs. on the body and adjusting accordingly). Field trials involving multiple users over longer durations would also be valuable to test system scalability and reliability in diverse real-life conditions. Finally, integration with network communication protocols could be enhanced – for instance, using opportunistic connectivity (when the device finds a network, it can upload a compressed summary of the inertial data or get assistance data for the GPS receiver to speed up fixes). These extensions would further solidify the framework established in this thesis.

In conclusion, this thesis demonstrated a successful approach to power-efficient GNSS usage for pedestrian localization, directly addressing the needs of resource-constrained scenarios. The research outcomes show that it is possible to significantly extend device battery life while still providing critical location tracking when it matters most. By tying the technical achievements back to the human-centric use case, we ensure that these advances are not just theoretical but stand to make a positive difference in people's lives. The work completes a step toward genuinely autonomous, smart wearable systems that can support independent living and safety for individuals in any environment – no matter how constrained the resources may be. We finish this journey with the confidence that our contributions will inspire continued innovation at the intersection of machine learning, sensor fusion, and practical system design for the next generation of localization technologies.

7.3 Publications Derived from the Thesis

The following publications have been derived from this thesis:

- 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. 36865–36889, Apr. 2023, doi: 10.1109/ACCESS.2023.3266957.

- A. P. Junior, L. E. Díez, A. Bahillo, and O. S. Eyobu, ”A Resource-Efficient Approach of GNSS Activation for Pedestrian Monitoring,” in Mobile and Ubiquitous Systems: Computing, Networking and Services, Melbourne, Australia: Springer Nature Switzerland, Jul. 2024, pp. 526–546. doi: 10.1007/978-3-031-63989-0_28.
- A. P. Junior, L. E. Díez, A. Bahillo, and O. S. Eyobu, ”ML-Driven User Activity-Based GNSS Activation for Power Optimization in Resource-Constrained Environments,” IEEE Tran. (Under review)

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Declaration

I herewith declare that I have produced this work without the prohibited assistance of third parties and without making use of aids other than those specified; notions taken over directly or indirectly from other sources have been identified as such. This work has not previously been presented in identical or similar form to any examination board.

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