

BLE Beacon-Based Micro-Tracking Systems: A Review of Positioning Methods, Signal Processing, Applications and Research Challenges

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Abstract- Finding people or objects inside a building is not always straightforward. GPS works well outdoors, but walls and roofs weaken its signals indoors. This creates a need for affordable systems that can identify the room or area where a person or item is located. Bluetooth Low Energy (BLE) beacons are small, battery-powered transmitters that offer one practical option. This review examines 17 sources published between 2012 and 2024 on BLE-based indoor positioning and micro-tracking. The studies are organised around positioning techniques, RSSI fingerprinting, signal filtering, machine learning, Bluetooth 5.1 direction finding, and applications in places such as museums and hospitals. Overall, fingerprinting tends to perform better than estimating position from signal strength alone. In one testbed, 95% of position estimates were within 2.6 metres when the beacons were placed relatively close together. Filtering and machine-learning methods can make estimates more stable, while Bluetooth 5.1 direction finding may support more precise positioning. However, signal strength is affected by people and the surrounding environment, and many studies test their systems at only one site for a limited period. Battery replacement, ongoing maintenance and privacy also receive less attention than accuracy. The review compares twelve representative studies, summarises recurring research gaps and suggests practical steps towards reliable systems that can operate beyond controlled experiments.

Keywords— BLE beacon, micro-tracking, indoor positioning, RSSI fingerprinting, Bluetooth 5.1 direction finding, asset tracking, Internet of Things

I. INTRODUCTION

Satellite navigation is useful when the sky is open, but it becomes less reliable inside buildings. Walls, ceilings and other obstacles weaken GPS signals, so indoor systems often depend on local technologies instead. Wi-Fi, radiofrequency identification (RFID), ultra-wideband (UWB) and Bluetooth have all been used for indoor positioning. Earlier surveys show that no single technology is ideal for every situation: the best choice depends on the required accuracy, budget, coverage and energy use [1], [2].

BLE is appealing because its hardware is relatively inexpensive and simple to install. A beacon sends short wireless advertising packets at regular intervals and can run on a battery. It does not need a direct power connection or network cable, which makes it easy to place on walls, ceilings, shelves or equipment. Faragher and Harle highlight this

practical advantage over Wi-Fi for indoor location, while also noting the challenges created by BLE radio behaviour [3]. BLE was introduced with Bluetooth 4.0, and most modern smartphones can scan for beacon signals

In this review, micro-tracking means locating people or objects within a relatively small area. The term microlocation is also used for highly precise positioning—sometimes down to centimetres—and for services such as geofencing and location-triggered actions [5], [6]. Many real applications do not need centimetre-level accuracy; knowing the correct room or zone is often enough. This is one reason BLE beacons are worth considering.

General surveys of indoor positioning already cover a wide range of technologies [7]. Rather than repeat that work, this paper focuses on BLE beacon-based micro-tracking and the difficulties that appear when systems are used in real settings. The review explains

the main positioning approaches, compares reported results, identifies common challenges and outlines areas for future research. Section 2 describes how the literature was selected. Section 3 reviews the techniques and applications, Section 4 compares selected studies, Sections 5 and 6 discuss gaps and possible research directions, and Section 7 concludes the paper.

II. REVIEW METHODOLOGY AND LITERATURE SELECTION CRITERIA

1. Search strategy

The literature search began with a general web search engine. Relevant results were then followed to publisher websites and research repositories, including IEEE Xplore, MDPI, Elsevier, Springer, PLOS, BMC, PubMed Central, arXiv and university repositories.

Search phrases combined 'BLE' or 'Bluetooth Low Energy beacon' with terms such as indoor positioning, RSSI, fingerprinting, trilateration, Kalman filter, machine learning, direction finding,

angle of arrival, asset tracking, hospital, museum, proximity detection and energy consumption. Most selected studies were published from 2015 to 2024. Two earlier papers were kept because they provide useful baseline evidence on energy use and hospital tracking [15], [17].

There are limits to this search process. Searches were not recorded in Scopus or Web of Science, so the number of results returned by those databases cannot be reported.

For that reason, this paper should be read as a structured narrative review rather than a systematic review. Some relevant papers may have been missed, particularly if they are indexed only in those databases. In a few cases, only the abstract and openly available sections could be accessed; conclusions about those papers are therefore limited to the information available in those records.

2. Eligibility criteria

Table 1 summarises the criteria used to decide which sources to include.

Criterion	Included	Excluded
Topic	BLE beacon-based or BLE-inclusive positioning, tracking or proximity detection; relevant surveys and studies of BLE energy use or direction finding.	Studies using only other technologies, such as Wi-Fi-only or UWB-only systems, and purely outdoor positioning.
Evidence type	Peer-reviewed journal and conference papers, and surveys with a clear scope or stated method.	Vendor white papers, blog posts, unpublished theses and marketing material.
Verifiability	Bibliographic information confirmed through a publisher, DOI or repository page.	Records whose authors, publication venue or DOI could not be verified.
Publication period	Mainly 2015–2024, with earlier foundational studies retained where useful.	Superseded or duplicate versions.

3. Selection outcome

A total of 17 sources met the selection criteria. Twelve primary, evaluation or overview studies were

used for the comparison in Section 4, while five additional surveys supported the background and definitions. Each source was checked against a

publisher page, DOI record or repository entry. Statements about the Bluetooth specification are based on the secondary sources cited in this paper rather than on direct analysis of the specification documents.

III. LITERATURE REVIEW

1. Positioning methods used with BLE beacons

BLE indoor positioning studies commonly use one of four approaches. Proximity positioning identifies the nearest beacon and treats its known location as the user's approximate location. Trilateration estimates the distance to several beacons and combines those distances to calculate a position. Fingerprinting works in two stages: signal readings are first collected at known locations to build a radio map, and later readings are compared with that map. Direction-based methods estimate the angle from which a signal arrives. Each method involves a different trade-off between accuracy, cost and setup effort [1]. Zafari et al. also point out that energy use, availability, range, delay, scalability and cost matter alongside accuracy.

For trilateration, distance is often estimated from the received signal strength indicator (RSSI) using a log-distance path-loss model:

$$d = 10^{[(P_0 - \text{RSSI}) / (10 \cdot n)]}$$

Here, d is the estimated distance, P_0 is the RSSI measured at one metre from the beacon, and n is the path-loss exponent, which depends on the environment. The calculation is straightforward, but its accuracy depends on reliable input values. In buildings, reflections, walls, people and the way a phone is held can all change RSSI. As a result, many studies use fingerprinting or combine several methods rather than rely only on estimated distances.

2. RSSI fingerprinting and BLE signal behaviour

The work by Faragher and Harle illustrates both the potential and the limitations of BLE. They tested fingerprinting with 19 beacons across an area of about 600 m² and found that BLE readings were strongly affected by fast fading. Their study also

examined ways to reduce this effect, as well as the power required for continuous scanning. They varied beacon density, transmission power and transmission frequency. With one beacon per 30 m², 95% of single position estimates were within 2.6 m. When the density was reduced to one beacon per 100 m², the error increased to 4.8 m. The Wi-Fi system used for comparison had an error of 8.5 m [3]. The results suggest that adding beacons can improve accuracy, but it also increases installation and maintenance costs.

Zhuang et al. focused on positioning with a smartphone. Because BLE beacons transmit over separate channels and the signal strength can vary between those channels, they modelled each channel individually. They used polynomial regression to estimate distance, fingerprinting to estimate location, and outlier detection with an extended Kalman filter to combine the information [8]. Their approach shows that obtaining a stable location estimate often requires several processing steps to handle noisy readings.

3. Filtering and tracking models

A single RSSI reading can be misleading, so many systems smooth readings collected over time. Daniş and Cemgil modelled beacon tracking as a hidden Markov model. They estimated observation probabilities using a Wasserstein distance method and applied sequential Monte Carlo techniques for tracking. Their choice of fingerprinting was based on earlier findings that it could be more reliable and precise than trilateration [4]. In another example, Spachos and Plataniotis developed a museum guide that applies a basic Kalman filter directly on the smartphone, without depending on cloud processing [9]. The broader microlocation survey by Spachos et al. similarly explains the role of filters in turning raw beacon measurements into more useful location estimates [5].

4. Room-level classification and machine learning

Some applications do not need an exact coordinate. They only need to determine which room a person or object is in. García-Paterna et al. treat this as a classification problem: each room is represented by fingerprint readings collected during calibration.

Their system uses wall-mounted beacons and aims to keep both the beacon count and the hardware requirements low [10].

Machine-learning methods have also been tested for room-level tracking. Baejah et al. combined a wearable device with BLE beacons to support monitoring of older adults and people with dementia. They compared six models— XGBoost, LightGBM, Random Forest, k-nearest neighbours, support vector machine and a multilayer perceptron— and tuned them using Bayesian optimisation. XGBoost performed best, with an average accuracy, precision, recall and F1-score of 0.91. The complete process took about 1.35 seconds, showing that the approach could operate in real time [11]. Since relatively few studies report end-to-end delay, this is a useful result.

5. Bluetooth 5.1 direction finding

Bluetooth 5.1 added direction-finding features based on angle of arrival (AoA) and angle of departure (AoD). As described by Pau et al., a constant tone extension is added to the advertising packet. An antenna array can then measure phase differences and estimate the signal's direction. Their review discusses development kits and potential uses such as asset tracking and locating people, and includes preliminary results from a real setting [12]. Qian et al. evaluated AoA with commercial equipment in four different environments. They found that angle measurements varied with the surroundings, with the office environment giving the weakest performance [13]. Direction finding may offer greater precision than RSSI-based methods, but it requires antenna arrays and remains sensitive to the environment.

6. Applications and experience from real settings

Museums are a useful setting for BLE because a location error of a few metres may still be acceptable. Spachos and Plataniotis developed an Android application that uses beacon proximity to show information about nearby artworks and estimates visitor location from RSS readings. Their tests considered distance estimation, positioning and detection accuracy with up to four beacons. They

concluded that BLE beacons could support interactive smartmuseum services [9].

Hospitals present more demanding conditions. Yoo et al. reported on a BLE/Wi-Fi asset-tracking system tested in a university hospital, where 117 nurses used it over three months. Their findings highlight practical issues that may not appear in laboratory tests. Battery-powered active tags that transmitted continuously lost charge quickly, and users raised concerns about location accuracy, tags coming loose from equipment and the need for training [14]. Fisher and Monahan examined real-time location systems more broadly through a three-year qualitative study involving 23 hospitals in the United States and 80 interviews. They found that many systems did not work as well as expected and that organisational constraints affected deployment. They considered asset tracking one of the more practical uses, provided the system was rolled out across the hospital and centrally managed [15]. Although that study was not limited to BLE, its lessons are relevant to beacon projects.

Proximity tracing provides another example of the limits of signal-strength measurements. Leith and Farrell measured Bluetooth signal strength between mobile phones on a commuter tram while evaluating exposure notification rules. They found little relationship between RSSI and actual distance. One national detection rule had a 50% true-positive rate and a 50% false-positive rate, which the authors described as similar to selecting people at random [16]. These were phone-to-phone measurements rather than measurements from fixed beacons, but they show how crowded spaces and reflections can make RSSI an unreliable indicator of distance.

7. Energy use and deployment

Low energy consumption is one of BLE's main advantages. Siekkinen et al. measured BLE and ZigBee devices using a power monitor and developed simple energy models. Their results showed that BLE transferred more bytes per joule than ZigBee in their tests [17]. However, low radio energy does not remove every power concern: continuous scanning can consume noticeable smartphone power [3], and hospital tags may need

regular attention to prevent battery failure [14]. In practice, someone must still check, locate and replace beacons, so maintenance should be considered alongside the advertised battery life.

Table 2 summarises the main BLE positioning approaches, while Table 3 compares twelve representative studies. Their numerical results should not be treated as a direct ranking because the experiments used different buildings, beacon layouts, devices, tasks and evaluation measures.

IV. COMPARATIVE ANALYSIS OF EXISTING STUDIES

Technique	Main strengths	Main limitations	Sources
Proximity (nearest beacon)	Simple to implement; no calibration; suitable for content triggers and presence checks.	Provides only a rough location; accuracy depends on spacing between beacons.	[1], [9]
RSSI lateration	No site survey is needed; calculations are relatively lightweight.	Depends on the path-loss model; RSSI changes with people, device orientation and reflections.	[1], [16]
RSSI fingerprinting	Often more reliable than lateration; useful for room-level classification.	Requires a site survey; the radio map may become outdated; BLE signals fluctuate.	[3], [4], [10]
Fingerprinting with filtering	Produces steadier tracks and helps manage noisy measurements.	Requires additional design, processing and tuning.	[8], [4], [9]
Machine-learning classifiers	Can provide good roomlevel results and operate in real time.	Needs labelled training data; often tested in only one setting.	[11], [10]
AoA/AoD (Bluetooth 5.1)	Measures signal direction and may improve asset or people tracking.	Needs antenna arrays; results vary between environments.	[12], [13]

Study	Focus and method	Main finding	Reported limitation
Siekkinen et al., 2012 [17]	Measured energy use of BLE and ZigBee/802.15.4 devices.	BLE transferred more bytes per joule in the tested devices.	Focused on link-level energy, not positioning.
Fisher & Monahan, 2012 [15]	Qualitative evaluation of real-time location systems in 23 US hospitals.	Many systems had limited functionality; asset tracking was a practical use when supported by a hospital-wide rollout.	Not specific to BLE; qualitative study.

Faragher & Harle, 2015 [3]	BLE fingerprinting with 19 beacons in a testbed of about 600 m ² .	95th-percentile error was below 2.6 m at one beacon per 30 m ² , 4.8 m at one per 100 m ² , and 8.5 m for Wi-Fi.	Single testbed, fast fading and scanning power costs.
Zhuang et al., 2016 [8]	Smartphone positioning using channel-specific regression, fingerprinting, outlier detection and an extended Kalman filter.	Combined distance and fingerprint estimates in a filtered result.	More modelling and calibration are required.
Daniş & Cemgil, 2017 [4]	Hidden Markov model, Wasserstein-based observations and sequential Monte Carlo tracking.	Demonstrated BLE beacon localisation and tracking using fingerprints.	Needs fingerprint training data.
Yoo et al., 2018 [14]	BLE/Wi-Fi asset tracking tested with 117 nurses over three months.	User feedback highlighted location errors, detached tags and battery drain.	Feasibility study at one hospital.
Spachos & Plataniotis, 2020 [9]	Museum application using RSS readings and an onphone Kalman filter, with up to four beacons.	Beacon accuracy was suitable for a setting where errors of a few metres were acceptable.	One venue and relatively coarse accuracy.
Leith & Farrell, 2020 [16]	Phone-to-phone RSSI measurements on a commuter tram.	RSSI and distance were weakly related; one rule produced 50% true and false positives.	Phone-to-phone proximity rather than fixed-beacon tracking.
García-Paterna et al., 2021 [10]	Room-level classification using fingerprints from wall-mounted BLE beacons.	Showed how room location can be treated as a classification task with limited hardware.	Room-level results and site calibration required.
Pau et al., 2021 [12]	Review and preliminary testing of Bluetooth 5.1 AoA/AoD.	Direction finding was identified as relevant to asset and people tracking.	Preliminary results; antenna arrays required.
Qian et al., 2022 [13]	AoA testing with commercial Bluetooth 5.1 equipment in four environments.	Angle measurement quality depended on the environment and was weakest in an office area.	Short tests and sensitivity to surroundings.
Baejah et al., 2024 [11]	Wearable device, BLE beacons and six machinelearning models for roomlevel positioning.	XGBoost achieved 0.91 for accuracy, precision, recall and F1, with about 1.35 seconds end to end.	One setting and roomlevel localisation.

Several patterns emerge from these comparisons. First, the accuracy needed depends on the application: a museum guide may work well with a few metres of error, while distinguishing neighbouring shelves requires more precision. Fingerprinting and machine learning have produced strong results, but both depend on calibration or labelled data, and the time and cost of preparing that data are rarely reported. Second, field studies reveal problems that controlled experiments can overlook, particularly battery life, tags coming loose and unreliable readings around people. Finally, the studies use different sites and measures, so it is difficult to make a fair, direct comparison between their results.

V. RESEARCH CHALLENGES AND IDENTIFIED GAPS

1. Main challenges

The most persistent technical challenge is the instability of BLE signals. Fast fading and changes in device orientation, nearby people and the surrounding structure can all affect RSSI [3], [16]. Filtering and machinelearning methods help reduce the impact, but they do not remove the underlying problem.

Calibration and maintenance are also important. Fingerprinting requires measurements to be collected at known points before the system can be used. If the room layout changes or beacons are moved or replaced, the stored radio map may no longer represent the environment. Although fingerprinting studies describe calibration as part of their methods, few measure how frequently it must be repeated [3], [4], [10].

A third challenge is the ongoing work involved in energy and tag management. BLE can use little energy at the radio level [17], but real deployments still need staff to check batteries and ensure that tags remain attached to equipment [14]. Deployment also involves organisational decisions. The hospital research by Fisher and Monahan found that whole-site implementation and central management could be difficult, even when the technology itself was available [15].

Privacy deserves equal attention, especially when the system tracks people rather than equipment. Location history can reveal sensitive details about someone's movements, yet privacy is not a central evaluation measure in most of the positioning studies reviewed here. The findings from proximity tracing also show that weak accuracy can affect public confidence in a location-based system [16].

2. Identified research gaps

Research gap	Evidence in reviewed work	Why it matters
Short tests at a single site	Many studies use one testbed, museum, room set or hospital [3], [9], [10], [11].	Results may not carry over to different buildings, layouts or seasons.
Unreliable RSSI around people	Fast fading in testbeds and a weak RSSI-distance relationship in a tram were reported [3], [16].	Distance estimates and proximity thresholds may give misleading results.
Calibration and radio-map upkeep not costed	Fingerprint-based approaches rely on calibration data [3], [4], [10].	Maintenance effort can grow as the site gets larger or its layout changes.
Limited reporting of energy and tag management	Scanning power costs and tag battery drain were discussed in only some studies [3], [14].	Battery replacement can become a major part of long-term operating costs.

Limited testing of direction finding	The reviewed evidence includes an overview and a comparison across environments [12], [13].	The extra hardware cost needs to be weighed against the accuracy gained.
Real-time delay rarely reported	Only one of the compared studies reported end-to-end processing time [11].	A location result is less useful if it arrives too late.
Privacy and consent not routinely assessed	Most positioning studies in Table 3 give little attention to privacy.	Tracking people creates legal, ethical and trust responsibilities.
No shared BLE tracking benchmark	Studies use their own sites, beacon arrangements and performance measures.	It is difficult to compare methods fairly.

VI. PROPOSED RESEARCH DIRECTIONS

The following directions are suggestions based on the gaps identified in the reviewed literature; they are not results from a system developed or tested for this paper.

1. Test systems across sites and over longer periods

A useful next step would be to test the same BLE system in several buildings over weeks or months, using independent ground-truth measurements. Longer trials could show how quickly fingerprints become outdated, how crowds affect the signals and how often recalibration is actually needed.

2. Share datasets and use common evaluation measures

Researchers could make results easier to compare by sharing BLE measurements alongside beacon layouts, device models and verified reference locations. Evaluations should report error percentiles, room-level accuracy, processing delay, energy use and the effort required to create and maintain the radio map.

3. Combine methods where they are most useful

A hybrid system could use proximity or room classification for rough location, fingerprinting with filters for more detailed estimates, and angle-based measurements only in areas where higher precision is needed. This approach could avoid installing expensive hardware everywhere. Whether Bluetooth 5.1 direction finding offers enough benefit to justify

antenna arrays in ordinary buildings remains an open question [12], [13].

4. Make deployment easier to maintain

Practical systems should monitor beacon battery levels, adjust advertising and scanning intervals to suit actual use, and make it easy for staff to identify a failed beacon. Battery-life results should be measured under realistic operating schedules rather than relying only on manufacturer estimates.

5. Process data near the user when possible

The museum study's on-phone Kalman filter [9] and the real-time machine-learning approach used in healthcare [11] point towards processing some information on the phone or at the network edge. Filtering and classification can happen close to where readings are collected, reducing the need to send detailed location histories to a central server. Only the information needed by the application should be transmitted.

6. Include privacy from the beginning

A tracking system should collect and retain as little location history as possible. Pseudonymous identifiers, clear information for users and a practical way to opt out can help reduce privacy risks. These features should be treated as system requirements and evaluated alongside positioning accuracy.

7. Outline of a possible system pipeline

Based on this review, a future experimental system could work as follows: beacons attached to equipment or installed around a building broadcast

their advertising packets; phones, scanners or gateways collect the signals; a local processing stage removes outliers and filters noisy readings; and a positioning engine estimates the room or zone and reports its confidence. The application then uses that estimate. Periodic reference measurements can be used to check whether the radio map remains accurate and to update models when needed. This pipeline is proposed as a starting point for future experiments and has not been built or evaluated in the present review.

VII. CONCLUSION AND FUTURE SCOPE

BLE beacons provide a relatively affordable way to track people and objects indoors. The studies reviewed here show that fingerprinting, filtering and machine learning can support room-level positioning and metre-level estimates under suitable conditions. Increasing beacon density can improve accuracy, although it also raises the cost of installation and upkeep. Bluetooth 5.1 direction finding may support more precise measurements, but its performance still depends on the environment and the required antenna hardware.

The literature also makes clear that good results in a controlled test do not guarantee reliable performance in everyday use. People and reflective surfaces can distort RSSI, and many studies have not tested their methods beyond one site. Calibration, battery replacement, maintenance and the practical work of deploying a system across an organisation are also underreported. Privacy is especially important when individuals are being tracked.

Future research should focus on systems that remain useful in real buildings over time, rather than only trying to improve accuracy in a single experiment. Multi-site trials, open datasets, shared evaluation measures, energy-aware design, local processing and privacy safeguards would make results more useful to researchers and practitioners. A follow-up study could extend the search through logged Scopus and Web of Science queries, consult vendor-neutral technical specifications and test a small pilot system—for example, tracking equipment across

several rooms in a laboratory or hospital ward with verified reference locations.

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