Self-calibration and Collaborative Localization for UWB Positioning Systems: A Survey and Future Research Directions

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Ultra-Wideband (UWB) is a Radio Frequency (RF) technology that is currently used for accurate indoor localization. However, the cost of deploying such a system is large, mainly due to the need for manually measuring the exact location of the installed infrastructure devices ("anchor nodes"). Self-calibration of UWB reduces deployment costs because it allows for automatic updating of the coordinates of fixed nodes when they are installed or moved. Additionally, installation costs can also be reduced by using collaborative localization approaches where mobile nodes act as anchors. This article surveys the most significant research that has been done on self-calibration and collaborative localization. First, we find that often, these terms are improperly used, leading to confusion for the readers. Furthermore, we find that in most of the cases, UWB specific characteristics are not exploited, so that crucial opportunities to improve performance are lost. Our classification and analysis provide the basis for further research on self-calibration and collaborative localization in the deployment of UWB indoor localization systems. Finally, we identify several research tracks that are open for investigation and can lead to better performance, e.g. machine learning and optimized physical settings.

Additional Key Words and Phrases: survey, indoor localization, Ultra-Wideband, self-calibration, collaborative localization.

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1 INTRODUCTION

Location awareness in Radio Frequency (RF) systems provides a (mobile) node with its spatial coordinates, be it relative or absolute. This allows a variety of features such as location-based routing and scheduling, which are well researched

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topics for Wireless Sensor Networks (WSNs) [94, 119]. The diverse application scopes make these systems highly domain specific.

In the last couple of years, interest has grown in a particular technology called Ultra-Wideband (UWB) [30]. This is due to the availability of affordable UWB chips on the market. A rise that is culminating with the integration of UWB in one of the most popular consumer devices, i.e., the iPhone 11 from Apple. Additionally, UWB has been deeply researched and its accurate cm-level positioning capabilities are well known [106, 117]. Using this standard, position accuracy in the order of below 20 cm is possible. Unfortunately, nothing comes for free and UWB has a price to pay in terms of infrastructure installation costs and complexity, as well as robustness to non-line-of-sight (NLOS) conditions [26], which are typical features of indoor environments. This translates to problematic situations in which the fixed anchor nodes must be precisely surveyed for the system to properly work, and moreover, enough of them must be installed for good network coverage, i.e., all mobile nodes can communicate with the fixed ones.

In general, an UWB localization system is made of two types of node, i.e., the anchors and the tags. In the most frequently used anchor-based scenarios, the distances between the tags and the anchors must be known to pinpoint the position of the tags. Moreover, this calculation assumes the coordinates of the fixed anchor nodes to be already known to the system. This piece of information is normally retrieved by performing the so-called calibration procedure in which manual innervation is required to calculate the exact position of the fixed nodes. Several solutions [7, 18, 57, 83] show that for an average office size (in the order of 6x4 m^2) with LOS conditions, four anchors should be sufficient to track hundreds of tags and therefore the installation process is usually smooth and cost effective. Once enough fixed nodes have been placed, the tags can estimate the distances to each of the anchors and calculate their own locations using algorithms such as multilateration.

Nonetheless, several scenarios involve completely different environments, and requirements. Other than office spaces, UWB indoor localization systems are typically used in huge warehouses, wherein covering the entire space would require a large amount of hardware (anchors) and manpower to position (calibrate) all the fixed nodes. Another case in which a standard installation like in an office space would be problematic is an emergency situation. Indeed, UWB technology can be used during a crisis [31], e.g., fire or rescuing interventions. Clearly in these scenarios, it is almost impossible to foresee an infrastructure and even if one can be deployed, its installation and calibration should be kept as easy as possible to minimize installation costs and time.

To cope with the various situations in which UWB systems can operate, we need targeted mechanisms designed to work in any condition. Self-calibration allows easy deployment of anchor nodes no matter in which space is done, regardless of any requirements and possible restrictions. The system automatically detects an anchor and computes its coordinates. This technique can be also used when anchors are moved to new locations to update their positions. Similarly, when anchors are already pinpointed to their exact location and cannot be moved or if installing new ones is not permitted, the system can make use of collaborative localization. The mobile tags can exchange messages not only with the anchors but also with other mobile nodes. This can be crucial in different situations as we will show in Section 5 about possible problems. Similarly to self-calibration, collaborative localization aims to reduce the costs of the overall UWB system by keeping the infrastructure costs as low as possible and allowing peer-to-peer communication, i.e., tag-to-tag. We find that these two techniques are extremely important to make the UWB systems more mature and robust. However, self-calibration and collaborative localization are often wrongly interchanged concepts in standard practice. Moreover, in the majority of papers we came across [8, 26, 33, 38, 55, 56, 75, 90, 109, 119], authors are often not clearly defining the problem, nor are they UWB specific, in the sense that even when the topics are surveyed, it is never clear how UWB fits into the problem and how its specific characteristics can be exploited. This aspect will carefully be analyzed in the rest of the survey and in Section 6.3. We propose a classification that considers this and other aspects such as how information is distributed in the network and the type of algorithm adopted to position the nodes.

The main contributions of this paper are as follows:

- Solutions for both self-calibration and collaborative localization problems are rigorously surveyed. By emphasizing their differences and similarities, we establish that these are not the same.
- Most of the focus is given to UWB, which thanks to its characteristic features achieves high localization accuracies. The paper represents a generic tool for any indoor localization system designer, who might encounter similar problems.
- Future UWB research directions are described.

The following definitions remain valid throughout the paper and they are intended to help the reader understand the general concepts.

- **Anchors** are UWB nodes that form the infrastructure of the positioning system. They are typically installed in fixed locations.
- **Tags** are UWB nodes that can freely move in the deployment area.
- **Self-calibration** is intended as the automatic procedure that allows anchor nodes to precisely identify their own locations without additional interventions, e.g. manual measuring, or surveying. Typically, these nodes remain static after calibration.
- **Collaborative localization** is not only limited to anchor-tag communication, but it also involves peer-to-peer ranging, i.e. positioning is achieved without using fixed infrastructure nodes. In this case, the unlocalized nodes can be both tags and anchors.
- **Self-positioning / self-localization** is sometimes interchanged with the previous two terms. However, in this context we refer to it as the ability of a mobile node to calculate its own position, e.g., by passively listening to other communications happening. Moreover, this technique is performed at a given update frequency to track the position of the mobile nodes.

The rest of the paper is organized as follows. Section 2 presents related work. Section 3 analyzes the motivation of this survey more in detail. Section 4 outlines the most critical characteristics of UWB. Section 5 describes the problems and explain how they are typically tackled. Afterwards, section 6 reports the most significant research about the topic, followed by future work and the conclusion in section 7 and 8, respectively.

2 RELATED WORK

Previous localization surveys mostly investigated a wide range of metrics used to classify positioning methodologies. However, by looking at multiple aspects, some of the classifier are often overlooked. Even when collaboration is used to compare solutions, no further distinctions between self-calibration and collaborative localization are made.

2.1 Categorization using networks

Although a clear categorization to distinguish between self-calibration and collaborative localization is not yet found in literature, work on collecting and analyzing articles on wireless RF-based positioning does exist [12–14, 19, 21, 29, 32, 39–41, 45, 48, 51, 58, 61, 91, 111, 114, 116]. The more general studies on wireless positioning with traditional performance comparison metrics can be found in [13, 48, 58, 111, 116]. Chowdhury *et al.* [13] mainly classify localization algorithms based on mobility and infrastructure. More specifically, on whether a positioning algorithm is based on anchor nodes for which the initial location is given. Yassin *et al.* [111] provide an in-depth survey on cooperative localization in the sense of using multiple technologies, rather than the typical use of multiple unknown nodes collaborating within a single technology. This presents another gap within the classification of past survey papers and reinforces the need for a more thoroughgoing classification of the growing distinctions across cooperative localization systems. The use of UWB is discussed to a higher degree than other survey papers on indoor localization in [12, 51, 91].

Other studies, while maintaining traditional comparison metrics, have different main classifications. Surveys of wireless localization systems, which are based on mobile phones and mobile phone infrastructure are provided by [21, 61]. Maghdid *et al.* [61] present the main technical implementation challenges in smartphone localization technologies and solutions. The survey paper covers both the outdoor as well as indoor localization efforts, in addition to focus on seamless transition between outdoors and indoors.

The authors of [14, 19, 41] provide surveys with the focus on the processing performance of localization algorithms. Surveyed works by Coluccia *et al.* [14] are reviewed with three main comparison criteria: cooperation, mobility, and advances in signal processing. The cooperative localization methodologies are further subdivided as centralized or distributed.

The mobility of anchor nodes and unknown nodes are explicitly considered in [12–14, 39]. Chelouah *et al.* [12] use traditional performance metrics as the comparison criteria, with a focus on the mobility of sensor nodes in wireless sensor networks. A cursory classification of cooperative localization is one of the main comparison metrics in this paper. The classification excludes anchor-based localization methods from cooperative methods and limits the former to GPS-enabled devices.

Some comparison metrics for wireless positioning systems are defined by specific use-cases such as underwater localization [29] and emergency responds [32]. Ferreira *et al.* [32] provide the comparison of positioning systems by measurement type and localization methodology, with a particular focus on the requirements of emergency responders as comparison metrics.

2.2 Categorization using algorithms

The authors of [45, 51, 114] compare localization systems by the algorithms and methodologies used. Laoudias *et al.* [51] classify wireless localization systems based on measurement type, enabling algorithms, with a focus cellular networks, data fusion, simultaneous localization and mapping (SLAM), and user mobility. The discussion on cooperative localization is limited. Jang *et al.* [45] compare localization works based on traditional metrics and the algorithms used. The three main distinctions made are triangulation, fingerprinting with offline map creation and fingerprinting without offline map creation. More specifically, the focus lies on SLAM algorithms, distance-based position inferences, and crowdsourcing methods. Zafari *et al.* [114] provide a technology independent distinction between positioning principles across the state-of-the-art. The authors make a distinction in the aspect of cooperative localization, depending on the perspective of either the infrastructure or the device to be localized. These are respectively defined as Monitor Based Localization (MBL) and Device Based Localization (DBL). The authors provide a thorough coverage of UWB-based localization systems.

Several works have compared positioning systems based on whether offline training is required [41, 91]. Shit *et al.* [91] contain a wide variety of characteristics to compare each discussed localization method. There is a particular focus on localization methodologies that require offline training and those which do not. The classification itself is thorough in comparison to other works. The limitation of this survey paper lies in the restricted variation in surveyed technologies. UWB is not specifically mentioned.

Surveys on collaborative localization in wireless sensor networks can be found as well. Probably, the most comprehensive work on cooperative localization has been done in [75]. Authors surveyed numerous aspects such as type of measurements, calibration, synchronization, localization algorithms and briefly on connectivity issues. In [8], authors discuss theoretical limits, algorithms, and practical challenges for collaborative localization. Both range and angle-based techniques are surveyed and explained. Attention is also given to less popular topics such as unknown noise variance, NLOS, multipath propagation and synchronization. Another survey focuses more on the algorithmic aspects of positioning in collaborative networks [56]. Authors review popular algorithms based on maximum-likelihood estimation, convex relaxation and optimization and message passing. The preferred measurement type is Received Signal Strength (RSS), as it represents a good candidate for low cost applications [65].

2.3 Overview

Out the aforementioned 23 related works, 14 survey papers discuss cooperative localization, 10 papers explicitly classify by it and only [114] and [14] provide a further subdivision of cooperative localization. Similarly, positioning systems based on UWB are discussed in 12 of the reviewed survey papers.

We have shown that numerous surveys exist, but they focus mainly on non-UWB RF technologies. Moreover, none of the above studies explains nor highlights differences between self-calibration and collaborative localization. Even when these techniques are mentioned, they are not exhaustively analyzed, leaving space for a more detailed survey on these important topics for indoor positioning systems.

3 MOTIVATION

As outlined in the introduction, UWB is often chosen for its high accuracy localization capabilities. Many articles show that position accuracy of 20 cm or less is possible [11, 49, 62]. Moreover, the large amount of scientific literature produced several comparative studies, which mainly focus on the UWB standard, its positioning techniques and its applications [89]. In some cases, a short paragraph is dedicated to less ordinary issues such as cooperative localization [23]. However, this topic contains various aspects, which require extensive study. In fact, there exist several studies about cooperation and self-calibration for indoor localization systems, as shown in Section 2. Thus, we want to collect, analyze and report what has been done for the specific problem of collaborative localization in indoor localization networks and focus on UWB cases or understand if the principles are applicable to UWB, when it is not explicitly mentioned. To this end, surveys which are not specifically based on the UWB technology are also included. In parallel, the same is done for self-calibration as this is closely related to cooperation but in a specific positioning sense (to localize the anchor nodes) to improve and optimize the installation procedures , by minimizing time and costs. Moreover, we distinguish between self-calibration and collaborative localization concepts, which are sometimes misused or interchanged. In fact, calibrating the infrastructure nodes requires cooperation among nodes in the network but since it involves only fixed nodes, it is more correct to refer to it as self-calibration procedure. Section 5 clarifies what is meant with these two concepts and introduces the classification, which we adopted in the paper. However, before going into details, we introduce general concepts of the UWB standard to help the reader better understand the underlying technology and align the terminology to avoid ambiguities. We keep the following section brief as it is not the scope of this paper to dig into UWB technology itself as existing works have covered this thoroughly [27].

4 UWB STANDARD OVERVIEW

UWB uses extremely short pulses in time, which translate, as the name suggests, in large bandwidth, i.e. ≥ 500 MHz. The UWB PHY works with two different modulation schemes, namely single pulse modulation and burst position modulation (BPM) / binary phase-shift keying (BPSK). The UWB frame is then modulated in two separate ways, which have different robustness. This is a specific aspect of this technology and could be exploited to improve localization algorithms. In Section 6.3, we show a way in which this characteristic can be used to achieve better performance.
At the moment, the IEEE 802.15.4a is the reference standard for UWB communication. It allows UWB to work in the 3.1-10.6 GHz frequency band [70]. Since it operates in unlicensed bands, it is crucial to guarantee that UWB communication does not interfere with any other existing technologies such as WiFi in the 5 GHz band. Thus, Federal Communications Commission (FCC) establishes strict rules to ensure that UWB emissions remain small, i.e., low power spectral density (PSD) [98]. The Equivalent Isotropically Radiated Power (EIRP) limit is -41 dBm/MHz. This is an important aspect to consider when deploying UWB systems. Having low PSD has several implications, e.g., it could limit the maximum range the signal reaches still having high signal quality for localization purposes. However, UWB PHY defines the possibility to select among a large set of settings, which in turn will affect the performance in terms of accuracy, maximum range, and energy efficiency. These settings are:

- Frequency channel
- Pulse Repetition Frequency (PRF)
- Preamble length
- Bitrate

These are not the only things that can be changed but are the ones, together with the transmit power, that will influence UWB the most. This aspect is also discussed in Section 7.2 with regards to self-calibration and collaborative localization. Assuming that the best settings have been selected, which change from application to application, then UWB can be trusted in estimating distances with cm-level accuracy. By sending repetitions of short pulses, UWB can accurately timestamp incoming messages and more importantly distinguish peaks of the signals that belong to secondary paths. This is crucial in indoor environment where multipath propagation is the norm. However, a single distance is (almost always) useless to pinpoint the location of an asset regardless the environment. If 3D localization is the goal, then at least four separate distances are needed. An example of simple infrastructure with four anchors and one mobile tag is shown in Figure 2. The anchors are the devices that normally do not change their positions during the whole localization process, whilst the tag is the mobile asset that must be localized. In general, several techniques exist to do positioning in RF-based systems. These can be classified as shown in Figure 1. Scene analysis, proximity, and triangulation are

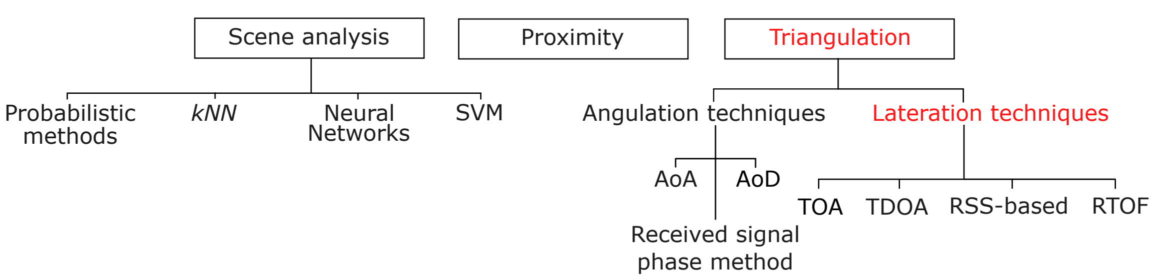


Fig. 1. Generic classification of approaches for localization systems. We focus on time-based solutions as specific case of range-based techniques [58].

three main categories that can be used to distinguish a localization algorithm as outlined in [58]. As UWB is often used in range-based systems, we focus on the triangulation category. This technique is in turn divided in angulation and lateration techniques. When the distances between two or more nodes are available, we differentiate based on how the distances are calculated and afterwards used. It can be done by looking at specific signal property, e.g., RSSI values [115] or by calculating the time that the signal takes to travel between the transmitter and receiver , known as Time of Flight (ToF) [37]. The former technique is typical of WiFi solutions, in which the location of the mobile asset is determined depending on the signal power levels of multiple access points [120]. On the contrary, thanks to the above-mentioned high timing resolution, UWB is often used in time-based distance estimation [88]. Moreover, UWB can either base the distance estimation on the arrival time at the receiver side (TOA) [35] or on the time difference of arrival among multiple receivers (TDOA). One of the most used distance measurement technique is two-way ranging (TWR). In TWR, tag and anchors are communicating in both directions. This exchange of messages can happen once, and this is called single sided TWR or it can happen twice, and, in this case, we talk of symmetrical double sided TWR (SDS-TWR) [83]. By accurately time-stamping the received messages (TOA) and calculating the ToF of each exchange, the distance between the devices can be estimated, assuming that the propagation speed is known. With this technique the range can be computed by the mobile nodes themselves and more importantly the anchors do not have to be synchronized. However, TWR requires more energy since all nodes are transmitting and receiving and more messages need to be exchanged. A solution to these two problems could come from adopting a TDOA approach. Hence, the scheme uses a one-way communication to achieve accurate localization. The mobile tag sends out a message that is then received by all anchors in range. These anchors must be accurately synchronized to be able to compute the difference in arrival times. Alternatively, the anchors can send out messages at specific non overlapping moments and the tag can compute the TDOA and therefore its own position. This technique has the benefit of reducing packet overhead, but time synchronization is crucial since a 1 ns error translates in 30 cm inaccuracy. In addition, TODA also results in lower latency compared to TWR, since a single measurement is received by multiple anchors. In TWR, it is not possible to perform measurements with more than one anchor at the time for a single transceiver. When the system exploits the direction of the propagating signal instead, we denote this as an angle-based solution. Typically, UWB works with the so-called Angle of arrival (AoA) algorithms [53, 68, 95, 108]. Multiple antennas are used to compare the estimation of the angles with the signal amplitude or the carrier phase, at which signals are received [1].

These are the general concepts used by UWB localization systems to track and localize mobile nodes. Although it seems straightforward to implement, there are many aspects to consider, especially when working in indoor environments. These aspects relate to signal propagation when subjected to obstructions, multipath and NLOS conditions. Despite the typical caveats of indoor localization, the characteristics of UWB provide opportunities to design solutions for aforementioned problems.

5 CLASSIFICATION CRITERIA

This section is intended to outline the classification criteria with which we survey the research on self-calibration and collaborative localization. UWB localization can be a simple task when a single tag is in LOS of 4 separate anchor nodes, as shown in Figure 2. However, sometimes anchors are physically obstructed by walls or metal structures creating NLOS conditions and reflections (Figure 3a). Furthermore, more generic scenarios consider multiple mobile nodes to be localized, as shown in Figure 3b. With the lack of sufficient anchors in range, a mobile tag's remaining option could be to cooperate with peer nodes to continue its localization efforts. This is a technique to which we refer as collaborative localization. Similarly, suppose there is a need to install additional anchors, e.g., to improve coverage in a specific area,

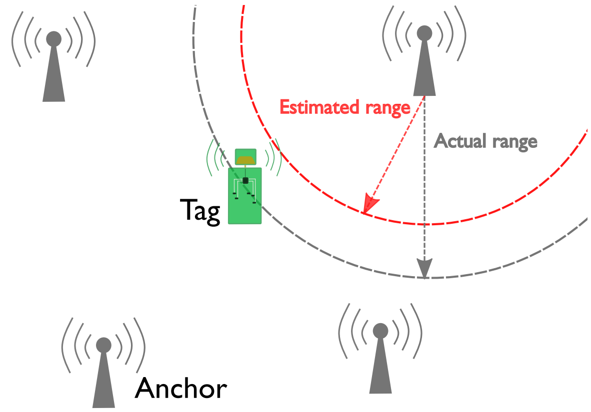
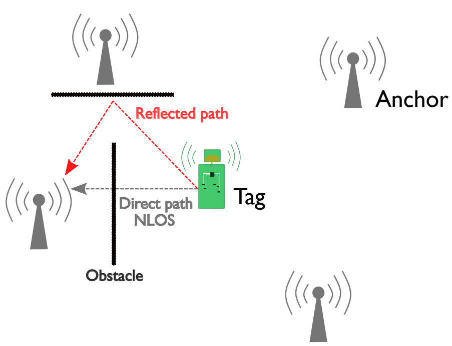
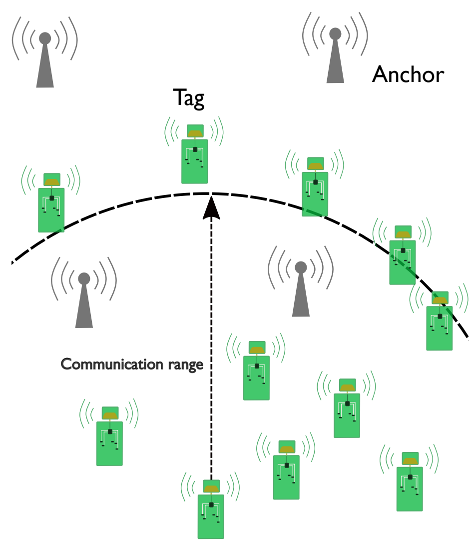


Fig. 2. Typical UWB ranging accuracy ($Actual - Estimated$) is in the order of 10 cm. By combining multiple ranges from different anchors, the mobile tag can be positioned.



(a) Multipath and obstructions, which generate NLOS conditions on the direct path between tag and anchors.



(b) Multiple mobile tags in a densely crowded environment. For certain tags, the number of anchors within communication range are insufficient.

Fig. 3. Typical indoor problematic scenarios.

or to install a whole new system, it should be possible to do so in an automatic and reliable way. Placing anchors without having to manually measure their locations is called a self-calibration procedure.

We analyze differences and highlight similarities among different solutions for both self-calibration and collaborative localization, based on multiple criteria. In Figure 4, we present our classification approach. Starting from the general problem of having to position nodes in a network, we assume that the nodes are ranging with each other. If these nodes are all anchors, then we distinguish between the hypothesis of already knowing their location or not. We refer to the

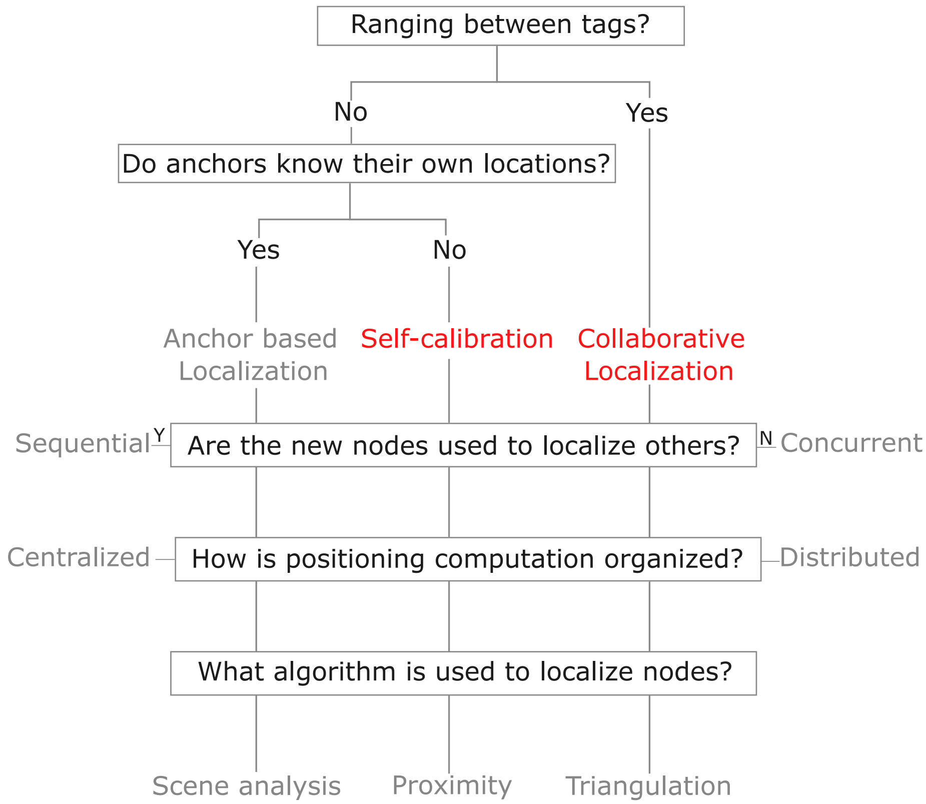


Fig. 4. Although the main distinction is between self-calibration and collaborative localization, we identify extra features that have an impact when designing such a system.

first case as regular anchor-based localization, while we define the problem of having anchors ranging and not knowing their coordinates, as **self-calibration**. On the other hand, if the nodes that are ranging are not only fixed anchors, but also mobile tags and we want to localize them, then we classify these as **collaborative localization** problems. Moreover, independently from the type of problem, we classify different solutions based on other aspects as well. First, whether the position is computed in a distributed or centralized manner. Second, we differentiate on how positioning information is propagated throughout the network. We call it sequential approach when, once a node has determined its own coordinates, it will contribute to pinpoint other unlocalized nodes. The opposite happens in the concurrent case, i.e. localized nodes are not used in the computation of the position of other nodes [8]. Finally, we report the type of algorithm that is used to solve the problem. The idea is to give the reader a full understanding of the state-of-the-art techniques that are used now to tackle the self-calibration and collaborative localization problems. In summary, both of the following approaches would be possible: (i) deploy more anchors and let them calibrate themselves using other nodes in the network (self-calibration) or (ii) let some of the mobile tags act as anchors (collaborative localization).

Our goal is to unify as much as possible literature to avoid confusion and misuse of terms. However, it is important to keep in mind that sometimes terms have different legitimate meanings and interpretations. For example, in [121]

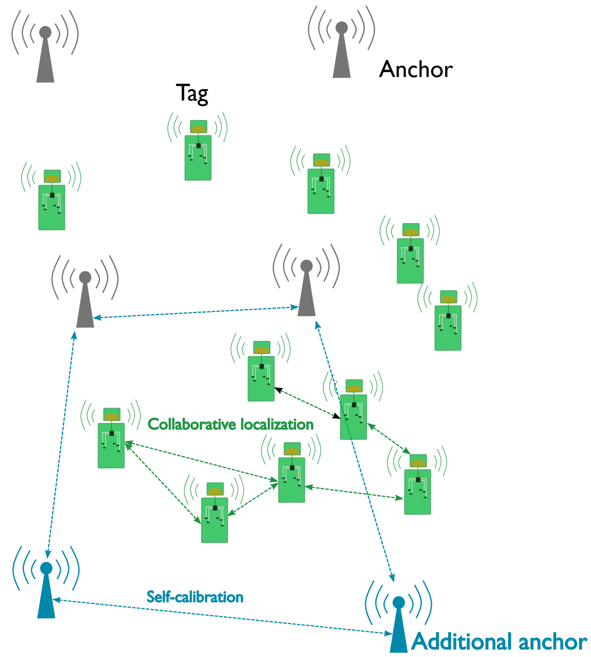


Fig. 5. Peers (tag or anchors) can talk to each other (collaboration) and additional infrastructure nodes, i.e. anchors, can be placed (calibration needed)

the authors refer to collaborative localization as the integration of different types of measurements, i.e. TOA- and RSSI-based.

In the next paragraphs, we explain in detail what is meant with each of the categories we have just presented. In Figure 5, we summarize the challenging conditions on which the systems operate. This image highlights a situation where few anchors are supposed to be used to localize many mobile tags. To manage such a scenario, more anchors can be installed to increase the coverage of the localization system (additional anchors) or alternatively, mobile nodes could be allowed to communicate to each other (peer-to-peer communication).

5.1 Distributed vs Centralized

Given the number of anchors and mobile nodes, the network can be organized in a distributed or centralized way. Typically, centralized networks require a backbone, which is used to deliver and collect all the information to a central point, e.g. to the localization server or engine. In contrast, in distributed networks all nodes participate in the position calculation [77]. Although distributed approaches are intrinsically more suited for nodes collaboration, centralized schemes are often used, e.g. when more computational power is required. Other aspects such as latency and overhead must be considered as well. Examples of network implementations for UWB systems can be found in [60, 82]. Both use a central entity and a separate backbone network to compute and deliver information to the UWB nodes, e.g. their time slots to transmit UWB packets. These are example of centralized schemes in which potentially latency and protocol overhead could limit the amount of node in the network itself.

5.2 Sequential vs Concurrent

This distinction involves unlocalized nodes, either anchors or tags. In sequential approaches, localized nodes act as anchors for unlocalized ones. In this scenario, even mobile tags, once their coordinates are known, are used to compute other nodes' positions, which could be both another tag and an anchor [8]. Conversely, concurrent behaviour means that once an unlocalized node has been localized, it will not be included to compute the position of other unlocalized nodes. The benefit of the concurrent approach is that errors will not be propagated to other nodes their positioning calculations. In sequential localization [8], a node has typically more chances to be localized as there are more available nodes that are considered for the position computation.

5.3 Type of algorithm

The last aspect we want to consider is the type of algorithm used to calculate the position of the unlocalized nodes, as classified in Figure 1. This is done to give the reader the opportunity to compare different solutions and to understand the potential of each of them, e.g., RSS-based localization (triangulation) could be applied both to WiFi and UWB standards. Some examples of most used localization algorithms are reported in Table 1, which also reports the type and the basic principle for each solution. Nevertheless, advanced algorithms sometimes consist of hybrid solutions in which two or more techniques are simultaneously used to solve the localization problem.

Table 1. Frequently used algorithms to solve localization problems

Algorithm	Type	Basic principle
Multilateration	Lateration	Estimating the location of the tag based on the time difference between signals arriving at different anchors [72]
Multidimensional scaling (MDS)	Scene analysis	An exploratory method that analyzes the dissimilarity of data for a certain set of objects [5]
Maximum likelihood estimation (MLE)	Scene analysis	A method that by maximizing the likelihood function, estimates the parameters of a probability distribution [50]
Kalman and particle filters	Scene analysis	Algorithms that uses noisy observation over time to estimate the state of an unknown variables [84]

5.4 Self-calibration vs collaborative localization

The most important and widely used solutions are presented in this section and the most relevant approaches for UWB (in which UWB characteristics may be exploited) are described more in depth. As already mentioned, this is the most controversial separation in literature. The difference between collaborative localization (involving both unlocalized tags and anchors) and self-calibration (exclusively among unlocalized anchors) is subtle but still very relevant. The main principle is the same: a node that does not know its position uses not only fixed anchors but also other localized nodes. Moreover, communications are not only between anchors and tags but also between peers, e.g. tag-tag or anchor-anchor. Whether these agnostic (not localized) nodes are both tags and anchors or exclusively anchors, defines the two problems, which are collaborative localization and self-calibration, respectively. We believe that these two cases must be differentiated because they also require different approaches. In an area wherein manual calibration is not suitable, whether an infrastructure needs to be expanded or is not present at all, the ability of the anchors to self-calibrate is crucial and must be as accurate as possible [71]. Moreover, all newly calibrated anchors must always support all tags, thus requiring sequential solutions to solve the calibration problem. In the collaborative localization approaches, all the fixed nodes , if present, are already in place with known coordinates and there is no direct need to add new ones, the mobile tags could help each other [20, 105]. A tag can also act as anchor to increase the accuracy of the system. However, Section 6 shows that the accuracy does not always increase for UWB systems, especially in critical scenarios, e.g., NLOS working conditions. When a mobile tag acts as anchor, the algorithm needs to be carefully designed to consider other related issues such as mobility of the node, reliability of its position and network synchronization.

Table 2. Summary of major studies on self-calibration and collaborative positioning for indoor localization systems

Solution	Nodes type	Topology	Type of algorithm	Sequential Concurrent	UWB specific	Exp. evaluated
Hamer *et al.* [38]	Anchors	Distributed	Triangulation	Sequential	Y	Y
Vashistha *et al.* [103]	Anchors	Centralized	Triangulation	Sequential	Y	Y
Batstone *et al.* [3]	Anchors	Distributed	Scene analysis	Sequential	Y	Y
Rajendra *et al.* [80]	Anchors	Distributed	Triangulation	Sequential	Y[1]	Y
Shi *et al.* [90]	Anchors	Not specified	Scene analysis	Sequential	Y	N
De Preter *et al.* [78]	Anchors	Centralized	Scene analysis	Sequential	Y	Y
Yu *et al.* [113]	Anchors	Not specified	Triangulation	Sequential	Y	Y
Dardari *et al.* [20]	Both	Not specified	Scene analysis	Sequential	Y	N
Maissner *et al.* [63]	Both	Not specified	Triangulation and scene analysis	Concurrent	Y[1]	N
Cai *et al.* [9]	Both	Centralized	Scene analysis	Sequential	Y	Y
Van de velde *et al.* [101]	Both	Centralized	Scene analysis	Sequential	Y	N
Van de velde *et al.* [100]	Both	Not specified	Scene analysis	Concurrent	Y[1]	N
Wymeersch *et al.* [107]	Both	Distributed	Scene analysis	Concurrent	Y	Y
Xu *et al.* [109]	Anchors	Centralized	Scene analysis	Sequential	N	Y
Patwari *et al.* [76]	Both	Not specified	Triangulation and scene analysis	Sequential	N	Y
Moses *et al.* [69]	Anchors	Centralized	Triangulation and scene analysis	Sequential	N	N
Doherty *et al.* [28]	Both	Centralized	Triangulation	Concurrent	N	N
E. Larsson [52]	Both	Distributed	Triangulation and scene analysis	Sequential	N	N
Costa *et al.* [16]	Both	Distributed	Scene analysis	Sequential	N	Y
Savvides *et al.* [86]	Partial	Centralized	Triangulation	Sequential	N	Y
Čapkun *et al.* [10]	Anchors	Distributed	Triangulation	Sequential	N	N
Ihler *et al.* [43]	Partial	Distributed	Scene analysis	Sequential	N	N
Kim at al. [47]	Partial	Distributed	Triangulation	Sequential	N	N
Fox *et al.* [33]	Anchors	Distributed	Scene analysis	Sequential	N	Y
Mekonnen *et al.* [64]	Anchors	Centralized	Scene analysis	Sequential	N	N
Crocco *et al.* [17]	Anchors	Distributed	Scene analysis	Sequential	N	N
Priyantha *et al.* [79]	Anchors	Distributed	Triangulation	Sequential	N	N
Zhou *et al.* [118]	Anchors	Both	Scene analysis	Sequential	N	N
Jia *et al.* [46]	Both	Centralized	Scene analysis	Sequential	N	N
Li *et al.* [55]	Both	Distributed	Scene analysis	Sequential	N	Y
Vaghefi *et al.* [99]	Both	Centralized	Scene analysis	Sequential	N	N
Gholami *et al.* [34]	Both	Distributed	Scene analysis	Sequential	N	N
Yin *et al.* [112]	Both	Distributed	Triangulation and scene analysis	Sequential	N	N
Tomic *et al.* [96]	Both	Centralized	Triangulation and scene analysis	Sequential	N	N
Sathyan *et al.* [85]	Both	Not specified	Triangulation and scene analysis	Sequential	N	Y
Li *et al.* [54]	Both	Distributed	Scene analysis	Sequential	N	N

6 LITERATURE OVERVIEW

Table 2 lists an extensive overview of the major studies on both self-calibration and collaborative localization techniques [3, 9, 10, 16, 17, 20, 28, 33, 34, 38, 43, 46, 47, 52, 54, 55, 63, 64, 69, 76, 78–80, 85, 86, 90, 96, 99–101, 103, 107, 109, 112, 113, 118]. In the next paragraphs, we focus on those articles that already target UWB as main technology. Nevertheless, we extended the classification work by using two extra columns in Table 2, namely UWB specific and experimental evaluation. By doing so, the reader gets a more general understanding of each solution and should note that even when non-UWB specific, the concepts may also be applied to other technologies. This choice also reflects the idea of enabling future research directions by showing that good work has already been done but there is still space for enhancement in Section 7. To emphasize the main differences between self-calibration and collaborative localization, we describe the

[1]UWB-specific features are used to improve accuracy and overall performance

two concepts in separate sections. An additional paragraph is dedicated to solutions that not only use UWB to validate their solutions but also design algorithms using UWB-specific features such as channel impulse response (CIR) or NLOS detection.

A wide variety of solutions (to the same problem) is reported in Table 2. These large differences among all papers make the performance comparison very challenging, as each implementation uses proprietary metrics. A solution to objectively compare the performance of multiple solution is outlined in [102]. Authors present the EVARILOS Benchmarking Platform. The idea is to enable automated evaluation and comparison of multiple solutions in different environments, by introducing a testbed-independent benchmarking platform, combined with multiple testbed-dependent plugins. However, such an objective evaluation method was not used for most of the scientific papers discussing the algorithms that we considered. Therefore, we report results mainly in terms of accuracy and we indicate, as clear as possible, the conditions in which each evaluation took place, e.g., in Table 3 we list the environment, the operating conditions and the size of the area for each study.

6.1 Self-calibration with UWB

When fixed anchor nodes are deployed with their positions unknown to the system, there is a need to calibrate the anchors in the sense of determining their locations to localize a mobile asset in any indoor environment. Their positions can be absolute or relative to each other. Either way, the calibration procedure can be carried out manually with special equipment (laser meters, camera, etc.) or in an automated way. If no manual intervention is required or possible, we refer to self-calibration procedures. As shown in Figure 1, localization is generally achieved with multiple techniques and types of data. However, works on self-calibration with UWB as listed in Table 2 are based on range measurements. Thus, to compute the location of the unlocalized anchors, the system must first know the distances between anchors. Once these are collected on a central point or across all nodes, different algorithms can be applied to compute the position of the anchors. The self-calibration problem requires a sequential approach. In fact, positioning any other mobile tag can be achieved by using the newly localized anchors. Various self-calibration approaches using UWB are reported in seven of the studies in Table 2 [3, 38, 78, 80, 90, 103, 113]. All of them are designed and/or validated using UWB indoor localization solutions. The main assumption is that no infrastructure is deployed. Mobile tags use anchors that are being calibrated by means of self-calibrating anchors. Therefore, the first step of these systems is to (self) calibrate the fixed anchor nodes to create a reference system. However, there exist various approaches to solve the issue.

In [38], the algorithm to self-localize the anchors is a distributed and iterative approach in which three anchors are initialized to define the reference system using the messages exchanged among them. After this first phase, the position estimates are further refined using distributed gradient descent. Ultimately, each anchor communicates its position to all other anchors in the network. The authors do not exploit any UWB-specific characteristic that could improve the performance of their solution. However, they reported experimental results with a position Root Mean Square Error (RMSE) of 97 mm to self-localize 8 anchor nodes [38]. Moreover, the mobile nodes can calculate their positions using TDOA by passively listening to the messages exchanged among the anchors, assuming that the system is accurately synchronized. The adopted scheme is a distributed and sequential solution using range-based measurements.

The idea to adopt TDOA is also used in [103], wherein a sequential and centralized low-cost self-calibration scheme is designed. Assuming the nodes are synchronized, the authors let the anchors range with each other (using a predefined transmission scheme) and by further computing the Differential TDOA (DTDOA), any anchor can be calibrated and its coordinates used in the positioning of mobile nodes (sequential solution). This solution is experimentally evaluated with up to 4 anchors. The distances used between the anchors were 5, 7, 10 and 15 meters in a controlled office environment.

Compared to the TDOA solution presented in [38], the RMSE was significantly larger from 17 cm up to 31 cm when calibrating 4 anchors.

Another sequential but this time distributed UWB research that assumes unknown the spatial coordinates of the anchors, is presented in [3]. In this study, a novel RANSAC approach with outliers and missing data was constructed and experimentally evaluated with UWB drones. As for previous work, the authors tested their solution in a small room with MOCAP system and obtained accuracy of around 11 cm for 6 anchor nodes. However, they then tested the deployed the same anchors to office space with multiple rooms and despite a 49.61% of data missing, due to more challenging environment, they still achieved better results than what was reported in [103], i.e. a mean accuracy of 13 cm.

An easy-to-use strategy for anchor self-localization is the focus of [90]. The positions of the anchors are automatically derived by combining UWB ranging estimations and low-cost Inertial Measurements Unit (IMU) data. This is the first solution we describe that uses other type of sensors rather than only UWB distances to compute the position of the anchors. The applied sequential method is based on SLAM technique and utilizes Error-State Kalman Filter (ESKF) to fuse UWB and IMU readings, resulting in UWB anchor position estimates and six Degrees of Freedom (6DoF) tag pose estimates. Given the different nature of the algorithm with respect to [3, 38, 103], for the system to work properly, freely moving the tag in the space of interest is the only thing that is required. Such a theoretical model is validated with several simulated experiments and 5 anchors, which show a typical RMSE of less than 15 cm in each space component, which is in line with what other studies have obtained in similar conditions.

Instead of solely relying the ranging capabilities of UWB, in [78], the authors also look at exploiting and modelling the UWB bias. A range bias correction is applied to distance estimations used in the auto-calibration technique presented. Implementing a centralized MLE algorithm, the authors achieve accurate positioning of mobile nodes, with an average error of 9 cm, using the auto-calibrated anchors, thus using a sequential solution. In this analysis, the authors used 4 anchors to test their solution as other evaluation we presented did as well. They also outperform previous solutions in terms of accuracy. However, the algorithm uses a second technology, namely RTK-GPS, to refine the initial guess of the anchors' locations. This is of course still a limitation for indoor scenarios wherein GPS signal cannot propagate.

Similar experimental results as in [90] are found in [113]. A two-process algorithm called SELF-CAL is proposed. Authors first apply Markov State Transition Equation (MSTE) to calculate the state vectors of all coordinates of the anchors and then, by using an iterative trilateral localization method, they calculate all the coordinates step by step in a sequential way. The calibration errors are once again averaging 10 cm in this solution. In addition, the authors showed that using the newly calibrated anchors and moving tag, the maximum dynamic error reported is less than 50 cm and the averaged error around 30 cm when compared to real track.

Overall, self-calibration with UWB allows to use many different types of algorithms as shown in the analysis. All the solutions we presented are range-based, to prove one more time that UWB typically works by estimating distances (or angles) between devices. Another common aspect is the relatively small number of anchors that are used to validate the system in experimental evaluations. Only in two cases more than 4 anchors are used [3, 38].This is an important aspect to keep in mind when analyzing the results in terms of calibration accuracy as adding more nodes, in much larger environments (more information in paragraph 6.4) could affect the performance of the algorithms. All surveyed works use sequential solution as expected since anchors are then used by other nodes in the network as reference points and the accuracies among different solutions are comparable, in the order of 20 cm localization errors.

6.2 Collaborative localization with UWB

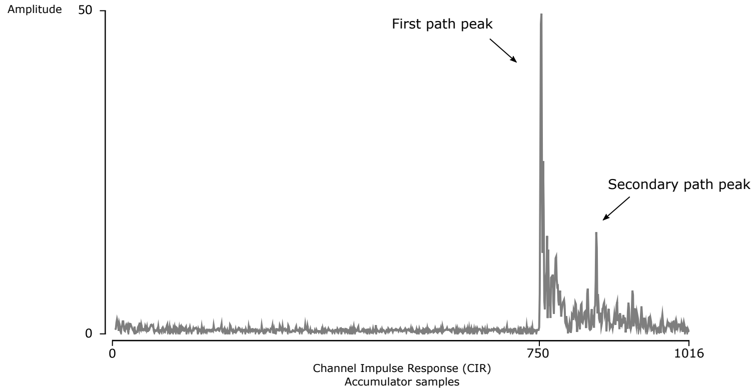
In collaborative localization, the key point and main difference with previous self-calibration concept, is that there is no requirement to have fixed anchor nodes with or without known locations. All nodes in the network are considered peers and are typically communicating with each other to exchange several information, such as the distances, to compute their positions. When the location is derived, nodes do not have necessarily to be used again to localize other devices, thus concurrent solutions are in this case possible. A distributed approach would be the more logical to solve the cooperation problems in wireless networks, however limited computational capabilities and power could be the bottleneck for distributed collaborative algorithms, especially for the mobile nodes. Thus, some of the solutions in Table 2 are designed with a centralized scheme [9, 101]. Once more, we focus on describing and comparing those solutions that have been designed and tested specifically for UWB. All the solutions that are presented in this paragraph use iterative optimization algorithms. At each iteration step, the locations of the nodes are refined based on the current states. What changes from one algorithm to the other is the role of these newly localized nodes. If they are then used in the calculation for other unlocalized nodes, then we refer to it as sequential solution. If not, we call it concurrent collaborative localization, as explained in Section 5.2.

The approach presented in [20] compares UWB situations in which collaborative (among mobile nodes) localization is either used or not used. In this circumstance the anchors are in place and their coordinates are known. Interestingly, if cooperation among tags is used, it does not mean necessarily improved accuracy. As a matter of fact, two things need to be considered when selecting mobile nodes as 'anchor': (i) whether LOS conditions were present or not and (ii) the geometry of the devices. Moreover, the used iterative LS algorithm showed that the geometric configuration of the nodes may have a stronger impact than the accuracy of the distances between nodes on the overall localization performance.

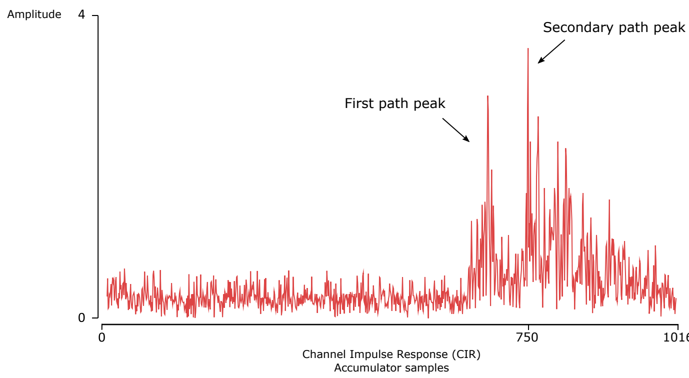
Authors in [9] suggest a strategy to improve localization accuracy in typical indoor NLOS environments. In line with findings of [20], they argue that normally, this kind of scenarios always leads to insufficient LOS ranging to perform multilateration and using NLOS measurements means large accuracy errors. To solve this, the authors avoid using NLOS rangings and use LOS between mobile nodes instead (in a sequential way). They define a non-linear optimization problem and use Simulated Annealing (SA) to solve it. Their approach is tested with commercial UWB hardware and errors in the order of 10 cm are reported when only LOS measurements are used (50% improvement from using NLOS estimations as well). The tests are conducted with 4 anchors and 2 unlocalized tags in a 10m x 5m environment.

In [101], message passing algorithms are compared to investigate the benefits of cooperative localization in NLOS conditions. More precisely, two algorithms called SPAWN (based on belief propagation) and SLEEP (expectation propagation) are described. To enable a fair comparison, the authors modified SLEEP to work with reduced network traffic and to include the reference nodes (ASLEEP version). Authors simulate a scenario with 100 users and 13 anchors using Monte Carlo simulations. The range of each anchor is fixed at 20 m in a total area of 100m x 100m. Although ASLEEP is less complex and requires less traffic than SPAWN, simulations show that SPAWN performs slightly better, in particular when increasing the percentage of NLOS messages. In LOS-only scenario, the difference with SLEEP is small and they both score around 50 cm error. These algorithms are both sequential, centralized and use range-based information.

We found another example of the use of SPAWN for collaborative localization. Authors in [107] present a fully distributed cooperative localization algorithm (SPAWN), which is also validated by means of realistic ranging models. Moreover, the solution is simulated with 13 anchors and 100 tags, same as in [101] but smaller area, i.e. 100m^2. Dealing



(a) CIR data from LOS conditions between two devices. The first path is well above other secondary peaks. Thus, timestamp can be accurately estimated.



(b) CIR data from NLOS conditions between two devices. The overall response is attenuated with respect to the above LOS case, even though PHY settings are the same. CIR analysis shows that secondary path come in stronger than the direct path, suggesting obstacles between transmitted and receiver.

Fig. 6. Channel Impulse Responses (CIRs) from DW1000 transceivers in different conditions, show different behaviour.

with mixed LOS/NLOS conditions is also investigated to evaluate the performance of the algorithm. However, the numerical results and the meter accuracy they achieved, leaves the question open to advanced investigation as results are far from what shown possible in [101].

We have shown that a great number of solutions that primarily focus on UWB already exists [3, 9, 20, 38, 63, 78, 80, 90, 100, 101, 103, 107, 113]. However, none of them in fact makes use of UWB-specific features (see Section 4) to boost the performance. Fortunately, there are some exceptions to this, and they are explained in the following passage.

6.3 Exploiting UWB characteristics

In Section 4 we outlined some of the most important characteristics of UWB. Without a doubt the main advantage of this technology is the ability to properly identify secondary paths in the received signal. Multipath propagation is commonly caused by reflections and scattering from obstacles in the vicinity of the transmitters and receivers. In Figure 6, a comparison between LOS and NLOS scenarios is depicted. Both plots report the CIR with a significant difference. In Figure 6a the first path is clearly identified, and its amplitude is the highest, thus making it easier for the receiver to timestamp the incoming packet, e.g., by using Leading Edge Detection (LDE) algorithms [73]. On the contrary, the overall CIR in Figure 6b is significantly more attenuated and the secondary peaks higher than the first one, which represents the direct path between transmitter and receiver. This second CIR is a clear indication that communication happened in NLOS conditions. Wrong peak detection could explain larger ranging errors in heavy NLOS conditions. However, predicting and correcting these errors, for example through Convolutional Neural Networks (CNNs), may boost the algorithm performance even in complex and larger solutions.

Moreover, UWB is particularly robust because of the different modulation schemes that it adopts. For both self-calibration and collaborative localization, it is important to know how many other nodes are available in a network, i.e., the so-called discovery phase. However, operating conditions are not always known nor static. Thus, the system might not know the best PHY setting to use to reach as many nodes as possible. Thanks to single pulse modulation, by receiving only the synchronization header (SHR), the full CIR can be recorded and all information attached to it can be extracted [36], e.g., LOS/NLOS, presence of obstacles, power associated with the response and so on. From this, the system can derive the best set of settings to use not only for the whole system but for each device-to-device pair, since each combination might be operating in different conditions. These and other aspects of unique UWB possibilities are described in Section 7.

Although attempts to improve accuracy of self-calibration and collaborative localization by exploiting specific features of UWB, these are typically limited to discard ranges that happened in NLOS conditions. In fact, in scientific literature, examples of this kind of approach can be found and the next two paragraphs are dedicated to these solutions.

6.3.1 Self-calibration. Differently from what we showed in Section 6.1, the authors in [80] uses extra features to improve the performance of the self-calibration. They propose a real-time, infrastructure free self-calibration scheme, which considers a highly connected network. The proposed method exploits UWB specific characteristics to filter NLOS communication links, simply by comparing total received power and the first path power. A theoretical ranging update rate of 50 Hz is proposed for a network consisting of 4 nodes. The authors do not provide a comment on the scalability of this method, which is based on a highly connected network. The proposed method reports experimental positioning errors less than 10 cm and a positioning update rate of 10 Hz. Even in more challenging NLOS environments, by looking at signal properties, the authors achieved comparable accuracy as in [3, 38, 78, 113], which are evaluated in LOS only.

6.3.2 Collaborative localization. A special solution for the collaborative localization problem is presented in [63]. Authors designed an algorithm that considers a characteristic of UWB signals: their channel impulse response (CIR), which among others, is typically used to decide whether the communication between two devices has happened in LOS conditions or not. Moreover, reflections can be easily isolated and filtered out. From this, knowing the geometry of the area they are covering, they use 'virtual anchors' (VAs) to locate the mobile nodes. VAs are virtual nodes, generated from signal reflections of known anchor nodes. Thus, authors tested their concurrent TOA-based solution with Kalman and Particle filters to localize mobile nodes and obtained accuracy of about 45 cm in typical indoor pedestrian scenario. Having virtual anchors, thus reducing costs of installing physical ones, also means lower accuracy if we compare these results to the previous ones in Section 6.2

The concept of VAs is also studied in [100], which introduces a low-cost two step algorithm called CUPID. This is also a case of concurrent TOA-based algorithm. It is claimed that even with a single anchor and exploiting collaborative localization among nodes, it is possible to perform accurate localization. Additionally, this is viable by integrating the floor plan, which produces a set of VAs. In the first step, exploiting collaboration among users, their relative coordinates are estimated and then (second phase) transformed to absolute coordinates. To this purpose, multipath components (MPCs), which are easy to extract thanks to the nature of UWB signals, are also considered for the absolute coordinate transformation. Simulations show good results in LOS condition, i.e. localization error < 30 cm. On the other hand, NLOS conditions cause a significant degradation of performance.

6.4 Reference environment

Table 2 includes a column to differentiate between algorithms that are experimentally evaluated and those that are not. Nearly half of the reported papers have done tests in real life conditions. In particular eight of the UWB specific works have done so [3, 9, 38, 78, 80, 103, 107, 113]. They all have in common the evaluation metric, i.e. the accuracy of UWB ranging and positioning but they differ in an essential aspect: the environment in which tests took place. As we outlined in Section 4, the surroundings are very important to assess the performance of UWB. Table 3 shows where these eight solutions where tested. Moreover, it highlights the operating conditions and the size of the area. Almost all of the

Table 3. Type of environment in which UWB is evaluated

Solution	Environment	Conditions	Size
Hamer *et al.* [38]	Office/Lab	LOS	6x7 m^2
Vashistha *et al.* [103]	Office/Lab	LOS	15x15 m^2
Batstone *et al.* [3]	Office/Lab	LOS	3x2 m^2
Rajendra *et al.* [80]	Building hallway	LOS/NLOS	22x20 m^2
De Preter *et al.* [78]	Open space (outdoor)	LOS	17x6 m^2
Yu *et al.* [113]	Office/lab	LOS	10x8 m^2
Cai *et al.* [9]	Office	LOS/NLOS	10x5 m^2
Wymeersch *et al.* [107]	Labs and hangar	LOS/NLOS	12x20 m^2

solutions are tested in an office space environment, in a very controlled scenario and reasonably small. Especially, those testing only LOS conditions [3, 38, 78, 103, 113] are on average performed in smaller spaces. Only four times, more challenging conditions (NLOS) were part of the tests. Still, the size of the environment is limited to around 10x15 m^2 on average, which is relatively small compared to other scenarios of interests such as warehouses and entire buildings.

7 FUTURE RESEARCH DIRECTIONS

Solid work on self-calibration and cooperation among mobile tags has been done as shown in Table 2. As we want to focus on a specific technology, i.e. UWB, we believe that much more could be achieved. Multiple research questions are still unanswered. Among others, we identify the following: (i) exploiting UWB ranging error estimation and correction, (ii) adapting the UWB PHY layer, (iii) compatibility, (iv) multiple evaluation metrics, (v) end-to-end system aspects and (vi) applications. In addition, the market growth, and the consequent opening to new sectors (UWB in smartphones), also brings new tasks especially related to self-calibration and collaborative localization, e.g. smartphone communicating to each other without infrastructure. The following paragraphs explain challenges and open questions on self-calibration and cooperation in UWB systems in more detail.

7.1 Exploiting UWB ranging error estimation and correction

UWB is uniquely suited for high accuracy ranging due to the use of short time pulses. An example of exploitation of these unique UWB features, can be found in [6], wherein the authors propose two methods to reduce localization error without prior knowledge about the radio environment. The authors propose the use of CNNs to (i) perform NLOS channel classification and (ii) to create ranging error regression models. Both methods can be used as additional input for self-calibration or collaborative localization, providing not only a range estimate but also an indication of the reliability off the estimation. Interestingly, it is shown how using raw CIR data outperforms approaches based on derived input signal features to detect NLOS conditions. Applying this to self-calibration or collaborative localization could significantly improve the performance of the two techniques we investigated in our analysis. Even more generally, other causes of errors could also be considered, providing much more information regarding the reliability of individual ranging measurements. Table 4 summarizes the most common sources of inaccuracies, many of which are not yet considered in self-calibration approaches. These causes of errors range from PHY-based aspects to network and application ones, highlighting the importance of a 'full-stack' approach when designing UWB systems. In literature [36, 66, 67, 92, 104], most papers focus on reducing the error of at most one of these causes of errors, while the majority of the solutions we presented in Section 6 do not correct the bias or error at all.

Table 4. Most common sources of errors in UWB localization systems

Cause of error	Possible mitigation approach
Pulse Distortion	Antenna and TX power calibration
Clock drift	Double sided TWR algorithm
Range Bias	Model to correct bias, e.g., on RX power
NLOS conditions	Including CIR in the range calculation
Latency	TDOA algorithm
Scalability	Scheduled access MAC protocols
Large DOP	Optimization of anchors placements

7.2 Adapting the UWB PHY layer

The possibility of using different physical settings for improving communication reliability has already been studied in [36]. The authors define a mechanism that changes settings such as channel, pulse repetition frequency, preamble length and data rate at runtime. Moreover, they also use the estimated CIR to measure the link quality of the environment and based on this, change, and adapt the PHY parameters. Experiments show increased communication robustness and energy efficiency, proving that this is a crucial aspect for IEEE 802.15.4a systems. Authors in [36] have shown that only the first part of the UWB frame is needed to record this information and adapt the PHY layer settings. This is important to claim that energy consumption can be kept low as reception of the full frame is not needed for certain phases of the self-calibration and collaborative localization processes, i.e., device discovery. However, all works related to self-calibration assume that the UWB device operates using a single RF configuration, and thus do not consider the impact of different UWB settings. For self-calibration, a possibility is to use higher TX power to reach a larger number of anchors and perform a more reliable calibration [25]. Nevertheless, the impact on accuracy and the possibility that the system would not be operating within legal limits have to be considered as well. In the user manual of the popular DW1000 UWB chip [24], there is already a suggested distinction between settings that should be used in LOS and NLOS. Table 5 reports these parameters. Preamble length, pulse repetition frequency and noise threshold multiplier differ

Table 5. Decawave suggestions based on the operational conditions, LOS or NLOS [24]

Parameter	LOS	NLOS
Preamble length	$\geq$ 128	$\geq$ 1024
Pulse repetition frequency	16 or 64 MHz	16 MHz
Noise threshold multiplier	13	12

between the LOS and NLOS case to basically exploits reflections and increase the sensitivity of the direct path signal in the NLOS cases. At the same times, these settings will increase the chance to erroneously trigger the reading of the incoming packet, which should be then corrected by the system. A self-localization system could continuously switch between different PHY settings to exploit the different range and accuracy trade-offs each of these settings offer. As such, the use of multiple UWB PHY settings to (i) increase the number of anchors within range and (ii) better correct environmental conditions will be beneficial to consider during self-calibration, making the measurements more reliable.

7.3 Compatibility

Currently, different commercial and academic UWB systems are designed independently of each other, using a variety of UWB settings, ranging approaches, MAC protocols and frame formats. To avoid a wild growth of incompatible ecosystems, there is a strong need for increased interoperability of future UWB systems. For this reason, several new industry alliances (UWB alliance [2], Fine Ranging Consortium (FiRa) [15], etc.) have recently been created with the aim of defining interoperability specifications for different application domains. One noteworthy initiative is the IEEE 802.15.4z standardization task force [87]. Besides defining future UWB PHY layers, the group is currently also designing new Information Elements (IE's) that can be added to existing IEEE 802.15.4 UWB frames, allowing negotiation of ranging methods and PHY settings between devices. Similar information elements could be defined for the purpose of negotiating the details of self-calibration and collaborative localization approaches, or to indicate a switch from localization to self-calibration.

7.4 Multiple evaluation metrics

The research papers [3, 9, 20, 38, 63, 78, 80, 90, 100, 101, 103, 107, 113] typically focus on improving localization accuracy. However, they do not consider other essential evaluation criteria that are relevant for realistic deployments, such as suitability for constrained devices, energy consumption, latency, etc. As such, there is a need to investigate existing trade-offs between performance and complexity. For example, researchers can look for drop-off points after which additional collected measurements result in diminishing accuracy returns or evaluate the memory and computational overhead of distributed solutions on embedded devices. In addition, studies on combining different positioning methods such as ToF, RSS and sensor fusion are also relevant to evaluate the impact of complex algorithms on accuracy, energy consumption and overhead.

7.5 End-to-end system aspects

Most scientific papers currently assume self-calibration to be an independent aspect of the whole system. In practice, self-calibration is merely an intermediate phase before (or while) the system is operational. As such, there is a need for self-calibration solutions that do not operate independently, while assuming no tags are being localized, but instead continuously verify and recalculate the location of the anchor nodes during the operational lifetime. To this end, messages that are being transmitted for localization or communication can be reused. As an example, backtracking particle filters have been proposed that are able to correct past location predictions of mobile tags based on more recent location estimates [4, 42]. Such backtracking algorithms [97], that aim to minimize the error of range estimates considering recent and past locations, could be modified to also correct the most likely position of the anchor nodes. As far as the authors are aware, such research about the optimal combination of operational aspects and auto-calibration phases is not yet explored.

7.6 Applications

Table 3 lists different environments in which UWB systems are deployed and tested in the considered scientific papers. Most of these scenarios are limited to small size offices and laboratories. However, many other applications are gaining interests. An example is automation for warehouses with drones autonomously flying in large spaces [59, 81]. These industrial environments are typically characterized by the presence of metals [22], which create multipath, reflections, diffraction, and obstruction. As shown in some works [9, 80, 107] UWB can pinpoint the location of the mobile nodes with good accuracy. However, more studies are needed to identify the feasibility of such a system in a large environment, having to cope with many technical constraints, e.g., size of the areas, obstacles, and speed of mobile nodes. Moreover, the integration of UWB in the iPhone 11 [44], which will probably be followed by other phone manufacturers, also indicates that UWB can be used for diverse application in the future.

Alongside industry 4.0 related applications, the new upcoming standard IEEE 802.15.4z [87] defines several new application domains. The security aspects of the new standard make the UWB technology suitable for keyless entry applications in automotive or building automation [74, 110]. For example, the mobile phone can act as key to open the door of the car by proximity detection. Similar concepts can apply to secure mobile payments. Temperature sensing in greenhouses is another concrete case in which collaborative localization among nodes could improve efficiency and performance of the operations [93]. Having dozens or hundreds of battery powered sensors collaborating to derive their own positions, could save time and money as the devices are sensing information that most of the time is position related, e.g., a specific area of the greenhouse gets too warm during the day and certain plants must be placed somewhere else.

Interestingly, UWB has proven to be a flexible standard that can be used in many situations. An example is also the social distancing application during the SARS-CoV-2. Solutions to provide accurate and reliable distances estimations to keep people far enough from each other have emerged. This is an interesting example of how peer-to-peer communication can take place with UWB, i.e., collaboration between nodes.

What works best in LOS conditions may fail when metal obstacles are present but still work when plants are obstructing the LOS between devices. Hence, it is crucial to exploit UWB related features to ensure that an optimal configuration is used in each type of application.

8 CONCLUSION

With many research articles on self-calibration and cooperation for indoor localization systems with focus on UWB, we decided to summarize the most researched approaches to give the readers the tools to better investigate and understand different opportunities. Features and possibilities of both self-calibration and collaborative localization are presented by separating the two concepts for a better understanding. Mainly the distinction between self-calibration and collaborative localization for UWB is resolved. Self-calibration indicates the specific procedure of acquiring/finding the coordinates of the infrastructure nodes, i.e. anchors. In contrast, in collaborative localization, the unlocalized mobile tags communicate with each other to estimate their own positions, i.e. without necessarily using a fixed infrastructure.

Although most of the reported solutions can be applied to a wide range of positioning technologies, we targeted those that used UWB to design and demonstrate the different application possibilities. We focused on UWB as its unique features represent a great potential for a wide range of indoor localization systems. Most scientific papers just treat self-calibration and collaboration problems as pure localization dilemma, and UWB-specific features, e.g. high timing resolution to mitigate multipath, are not exploited at all. As such, we listed a range of future research directions and strategies to better utilize UWB specific characteristics of the indoor localization problems. These include the use of better error mitigation models, the use of dynamic UWB PHY settings, providing UWB specific information elements for interoperability during self-calibration, considering multiple evaluation criteria while evaluating self-localization approaches, considering the interaction between localization and self-calibration phases and considering new application domains such as automotive. These directions will inspire future research paths for this promising domain.

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