Multimodal Indoor Localization: Fusion Possibilities of Ultrasonic and Bluetooth Low-Energy Data

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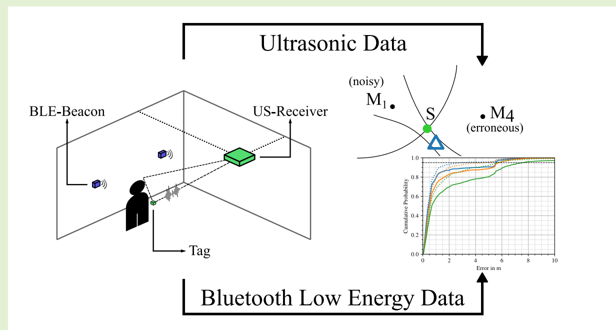
***Abstract*—The resilience of indoor localization systems is a main concern of their industrial application. A combination of different techniques can enhance the overall robustness of such systems. In this work, we present fusion possibilities of coarse Bluetooth Low Energy localization based on the received signal strength indicator and the finer ultrasound time difference of arrival (TDOA) technique. This approach offers the advantage to robustify the high-accuracy ultrasonic localization in areas with non-optimal coverage. Moreover, the data fusion enables to enhance the overall localization area in a cost effective manner. This contribution proposes and evaluates (i) novel methods of how the ultrasonic system can be extended to a constrained area and (ii) a novel possibility to incorporate available Bluetooth signal strength information in the TDOA algorithm to improve accuracy.**



***Index Terms*—Bluetooth low energy, indoor localization, received signal strength indicator, resilient localization, time-difference-of-arrival, ultrasonic localization.**

I. Introduction

IN TIMES of just-in-time networked production, the terms production and logistics are mostly mentioned in the same breath. Logistics costs account for about a quarter of a product across different industries. Therefore, attempts are often made to increase the savings potentials, especially since the logistics costs are scaled across various industries. A digital representation of the logistics process in Industry 4.0 factory is the basic requirement for modern and efficient process optimization that allows to monitor the process status and track goods flows and ongoing tasks. This requires precise, robust, reliable, and seamless localization of goods and robots. On the other hand, the installation effort of such indoor localization system should be minimal. Since most deployments require a heterogeneity in accuracy, it is feasible to use multiple localization technologies to optimize the cost versus accuracy target. Ultrasonic (US) localization technology may offer a competitive performance in most environments (see e.g. Table I) compared to other technologies but (1) is prone to error in fringe areas or from echos and (2) requires a high installation effort. These two problems are addressed in this paper. By adding another, more coarse localization technology, like Bluetooth Low Energy (BLE), it is possible to achieve a more optimal trade-off between accuracy and cost. Since such beacons are cheaply available and can simply be stuck to a wall, it would be desirable to be able to enhance the US system in low accuracy areas as well as extending the area of coverage with low effort (but with also less accuracy).

This paper is organized as follows: First of all, the related work to the topic is presented in Section II. A short system

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TABLE I
OVERVIEW OF INDOOR LOCALIZATION TECHNOLOGIES

Technology	Accuracy (m)	Coverage (m)	Measurement principle	Ref.
Cameras	0.0001 to 0.1	1 to 10	Angle from images	[2]
Infrared	0.6 to 2	1 to 5	Thermal imaging	[7]
RFID	1 to 5	2	Proximity detection	[2]
Wi-Fi	1 to 3	40	Signal strength	[5]
Bluetooth	1 to 3	20 to 40	Signal strength, angle of arrival	[8]
UWB	0.1 to 1	1 to 50	Time of arrival	[5], [9]
GNSS	10	*outside*	Time difference	[2]
Inertial sensors	0.2 to 1	10 to 100	Dead reckoning	[10]
Ultrasound	<0.15	30	Time difference	[3]

overview is then given in Section III, which discusses the main parts of our proposed system. The next section is concerned with the fundamental working principles of the different parts of our system. Section V discusses how different types of collected data are fused. Subsequently, we will demonstrate the performance of the Bluetooth one-dimensional (1-D) tracking as well as that of the overall system. Finally, Section VII draws the conclusions and gives an outlook for the future work.

II. RELATED WORK

Indoor localization has attracted increasing attention during the past decade, as the wide-scale proliferation of smart mobile devices (SMDs) has enabled a variety of location based systems (LBS) and applications including health management, surveillance, and marketing [1]. In general, there are a number of different signal modalities for conducting indoor localization [2]–[4]. While the ultra-wideband (UWB) and visible light communication technologies with high precision suffer from the requirements of additional equipment, relatively higher power consumption, and/or limited coverage, the achievable accuracy of many Bluetooth, Wi-Fi, and radio frequency identification (RFID) based systems is, however, only in the range of several meters. Such localization accuracy is too imprecise to meet the needs of the location-critical applications, like e.g. patient or asset tracking (several centimeters) [4]–[6]. Table I briefly summarizes the technologies used in indoor localization systems. Note that in most cases, only a single technology is used.

A. Acoustic Localization

Compared with the aforesaid signal metrics, sound has been shown to be more capable of conducting fine-grained indoor localization. This is mainly because: the sound propagation velocity is much slower than the speed of light and, hence, the timestamps of the received signals are easier to determine and higher localization accuracy is enabled. Nevertheless, as contamination is generally unavoidable for sound propagating in the complex indoor environments, signal detection on the receiver side can be troublesome. Actually, fine-grained LBS offering sub-meter precision remains a great challenge, especially in the scenarios where the working range is extended to several dozens of meters.

a) Localization Systems: Mandal *et al.* [11] present Beep, a Wi-Fi-synchronized time-of-arrival (TOA) based acoustic localization system which can attain the accuracy of 90 cm in 95% of the experiments. Ens *et al.*suggest a similar time-difference-of-arrival (TDOA) framework called ASSIST [12], in which the SMD emits sound signals in the frequency of 18 to 21 kHz. Wang *et al.*present an asynchronous acoustic localization system ARABIS [13] which adopts two-way ranging to remove the need for synchronization. 95-percentile localization error of 7.4 cm is reported in [13].

b) NLOS Mitigation: However, the anticipated positioning accuracy of the mentioned systems and approaches for localization will be guaranteed only when the connections between the SMD and base stations are under line-of-sight (LOS). The system performance can be seriously impaired in the presence of non-line-of-sight (NLOS) and/or multipath propagation. Indeed, there is still a yearning to devise serviceable indoor localization systems for industrial circumstances subject to plenty of adverse factors. Certain approaches give lower weights or discard unlikely measurements based on probabilistic motion models, additional sensors or, generally speaking, based on having more mathematical constraints than variables. In [14] a robust Extended Kalman filter is used to give lower weights to unlikely measurements. In [15] an interacting multiple model estimator is used. Specifically, two models are used, a model which assumes a high number of NLOS measurements and one which assumes only LOS measurements. Maximum correntropy based location approaches are also capable of mitigating the effect of non-line-of-sight measurements [16] and can also be combined with a Kalman filter when a certain motion model can be assumed [17]. Using relative signal amplitudes, a probabilistic algorithm for classification and rejection of NLOS signals, as shown by Haigh *et al.* [18] may be developed. In certain scenarios, non-line-of-sight signals can be modeled as virtual receivers which contain information about the position of the target and do not need to be discarded [19]. The presented works deal with the known interferences generally by having a high number of acoustic measurements, some of which are assumed to be in line-of-sight. In this work, we propose using further means of localization to mitigate those effects.

B. BLE Localization

The usage of BLE in the context of localization was first proposed Faragher and Harle [8] (localization by fingerprinting). The research on algorithms, both for fingerprinting, as well as for RSSI-Distance models, is still an ongoing topic.

c) RSSI-Distance Models: As for example, recently Alsmadi *et al.* [20] proposed a beacon weighting approach, extending the commonly used weighted centroid algorithm [21]. In that paper the authors add a Kalman filter to filter the RSS measurements. This approach fits to time series data, whereas in our paper deals with static measurements. As before a Bayesian approach is used to smooth the localization estimates. Pinto *et al.* [22] show the advantage of clustering the RSS fingerprints in several different log-distance models. This is relevant in larger settings with multiple different rooms, in our paper we try to address the problem of systematic errors in US systems, as well as the accurate localization in corridors. However our work may certainly be extended by a clustering approach.

d) Fingerprinting: As for fingerprinting techniques, Zuo *et al.* [23] propose a sampling method with a cart, as well as introducing different fingerprinting maps for different times of the day. More recently Ji *et al.* [24] proposed multivariable fingerprints for general fingerprinting-based localization systems, this approach is unfeasible for our system since only the raw RSSI was available.

e) Other Topics: A study on the RSSI measurement accuracy of different smartphones was presented by Boussad *et al.* [25]. Lee and Lin propose a localization system based in the variations of measurable RSS values, to track the entering and exiting of persons in rooms [26]. Another highly relevant topic is the placement of beacons, which is discussed by Rezazadeh *et al.* [27]. In contrast of placing several beacons, Li *et al.* [28] propose a RSS-based localization method with a single access point with three directional antennas. Jeon *et al.* [29] present a survey on commercially available beacons, their performance metrics and use cases.

C. Combined Localization

Utilizing multiple means of localization is a common topic in literature to achieve more accurate and robust results. Table II gives a comprehensive overview of combined localization approaches. A fruitful target is using smartphones for localization since they are usually equipped with a multitude of sensors like BLE, WiFi, acoustic, IMUs, cameras. Langlois *et al.* [30] present a comprehensive overview on how localization with smartphones, utilizing different sensors may be achieved. Several works have been proposed combining inbuilt sensors with infrastructure based localization technologies. One of the most straight-forward ways is using the RSSI of BLE nodes and combining the information with the data delivered by an IMU [31]. Similar approaches were investigated in [32]–[34]. Furthermore, Yu *et al.* [35] combine BLE with a inertial navigation system (INS) and PDR, to also obtain accurate heading and speed estimations. Another common concept is combining BLE and UWB, what allows for several different approaches. One is using a, with UWB, finely calibrated RSSI-map [36] and another is directly fusing the UWB measurements with the data of a RSSI-distance model [37]. Coded, visible light localization can provide high accuracy with centimeter accuracy, in addition with a signal strength signal or IMU the estimation can be made more robust against e.g. LED outages [38], [39].

The combination between ultrasound and BLE, as presented in this paper, to the best of our knowledge, has never been proposed before. Although both technologies have already been used in combination, where e.g. BLE is used to synchronize the ultrasonic signals [44]–[46] or in further combination with Light Fidelity (LiFi) [42], but never tightly coupled in the TDOA algorithm. Our main contributions are:

- Two algorithms to obtain a constrained location estimation with RSSI measurements.
- An algorithm to tightly integrate RSSI measurements directly into the ultrasonic TDOA algorithm to enhance the accuracy and robustness in fringe parts of the coverage area. The main advantage of this algorithm is that it uses the RSSI measurements to constrain the parametrized TDOA solution space by estimating the maximum distance at which the target can be from the beacons. Therefore, it assumes a realistic environment where the RSSI at a certain distance can vary due to changes in the environment, increasing the robustness of the estimations.
- An comprehensive experimental error analysis of the constrained algorithms as well as the fusion algorithm.

TABLE II
COMBINED LOCALIZATION APPROACHES

Authors	Combined Technologies	Ref.
Chen *et al.*	**BLE**, IMU	[31]
Liang and Krause	**BLE**, IMU, compass	[40]
Dinh *et al.*	**BLE**, PDR	[32]
Yu *et al.*	**BLE**, PDR, INS	[35]
Multiple	**BLE**, UWB	[36], [37]
Monica and Bergenti	UWB, WiFi	[41]
Guan *et al.*	LiFi, IMU	[39]
Thaljaoui and Khediri	**BLE**, **Acoustic**, LiFi	[42]
Yang *et al.*	**Acoustic**, IMU	[43]

III. SYSTEM OVERVIEW

A. Overview

The backbone of our system is the ultrasonic localization system ASSIST [12]. It consists of one or more tags, which are able to transmit ultrasonic chirps. These may then be picked up by receivers with known position. Fig. 1 shows the system concept. Due to multiple paths along which the emitted signal travels, the delay estimation might be heavily distorted. This happens in areas with sound-hard materials nearby. Intelligently placing the Bluetooth Low Energy (BLE) beacons therein, a multi-modal approach can be applied to reduce these distortions by utilizing the additional information provided by the BLE system. The BLE beacons transmit an advertisement signal with the period of t_{Adv}, which can be received by the tag to yield a received signal strength indicator (RSSI). The tag is connected by a 868 MHz RF communication link (through which RSSI values are transmitted and the tag is synchronized) to a central server on which the localization is performed.

B. Bluetooth

Bluetooth provides a simple and cheap way of adding further information to a localization system. BLE beacons are

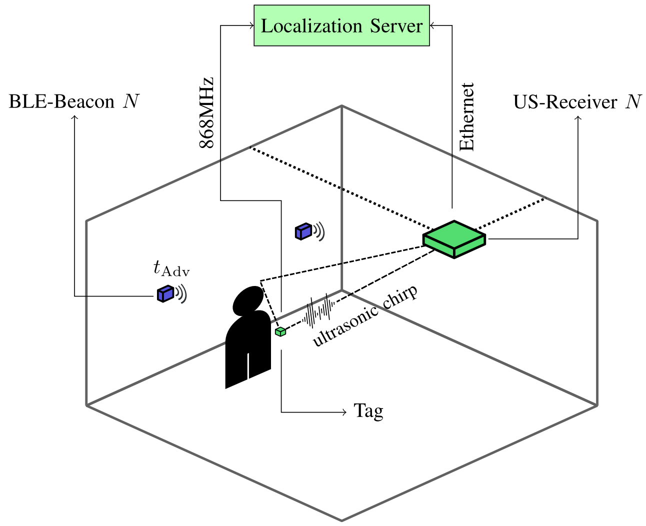

Fig. 1. System overview. The system consists of a tag able to emit ultrasonic chirps and receive BLE messages with their respective RSSI. Beacons are mounted in areas where the accuracy of ultrasonic system is decreased. Several ultrasonic receivers (US-receivers) are mounted to the ceiling to receive the signal from the tag. The tag as well as the US-receivers communicate with a central localization server on which the localization is performed.

now readily available, and easy to install. The advertising capability of BLE enables a beacon to broadcast identity messages without being paired to any other devices. The Bluetooth Core Specification defines 40 different channels (center frequency of channels is $2402\,\text{MHz} + k \cdot 2\,\text{MHz}$ for $k = 0, \ldots, 39$) of which three are used as advertisement channels [8]. A BLE beacon sends an advertisement package on one of these channels. This package, which contains an address and a payload, can then be received by any BLE-capable device. Usually, an RSSI is available on standard chips according to the payload. Our setup constrains itself on using only the RSSI and the beacon-identifying payload. Therefore, we do not use information concerning the channel (and respective frequency) or further information possibly available on the sample level.

C. Ultrasound

TDOA-based ultrasound positioning system is deployed in areas that require location information in higher precision.

In contrast to the majority of existing schemes optimizing some cost function over the Cartesian coordinates of sender position, we rely on the parameterization of hyperbolas, which are originally defined by the error-free TDOA information. We approximate the hyperbolas using the available but erroneous TDOA measurements, and aim to find a point thereon closest to all the other hyperbolas as the estimated sender location. A two-step strategy is put forward to fulfill the task. In our first-stage treatment, a parameterized nonlinear least squares (LS) estimation problem is to be solved. Next, we utilize a selection criterion built on a similar LS cost function to pick out the most plausible solution. It is worth noting that though derived based on the ℓ_2-space, our parametric method

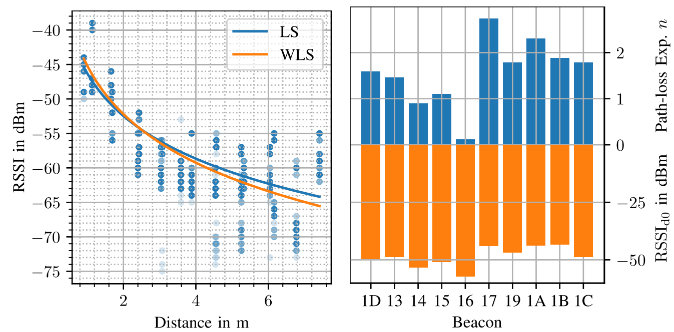

Fig. 2. *Left:* Progression of RSSI measurements over distance with LS and WLS fits with reciprocal distance weighting of Beacon 17. The fits yield the parameters ($n_{\text{LS}} = 2.06$, $\text{RSSI}_{\text{d0,LS}} = -46$ dBm) and ($n_{\text{WLS}} = 2.34$, $\text{RSSI}_{\text{d0,WLS}} = -45$ dBm). *Right:* LS parameter fits of the path-loss exponent n and the signal power RSSI_{d0} for different beacons. The path-loss exponents are varying significantly in contrast to the calibration signal powers.

possesses a higher level of robustness against outliers than the traditional ℓ_2-space-based approaches.

IV. Fundamental Working Principles

In this section, the fundamental working principles and how the localization is performed and implemented in both systems is detailed. First, some fundamentals about the Bluetooth-based localization is presented and then the details of the utilized ultrasonic localization system.

A. Localization With Bluetooth

With the ever-increasing availability of BLE devices, the field of BLE localization has attracted significant research interest. The RSSI, which is generally available on the devices, is dependent on the distance between sender and receiver. The basic problem is to estimate the location by utilizing this indicator. There are two general tasks based on the RSSI, known as the distance estimation by signal attenuation and fingerprinting. We summarize the detailed methods as follows.

1) Location Estimation by Multilateration: The signal attenuation by the distance can be described with the Friis Free Space Path Loss (FSPL) model. The quadratic path-loss exponent can be generalized to a tuneable number n depending on the operation environment. Furthermore, with the assumption of isotropy of both the transmitter and receiver antennas, the model in (1) may be calibrated by a certain signal power RSSI_{d0} at the distance d_0 [20]:

$$\text{RSSI} = \text{RSSI}_{\text{d0}} - 10\,n\log\left(\frac{d}{d_0}\right) \tag{1}$$

Fig. 2 shows recorded data with LS and weighted LS (WLS) fits of the model, and illustrates the LS parameter fits of the path-loss exponent n and the signal power RSSI_{d0} for different beacons. By inverting this relationship, a point estimator can be derived which delivers a distance estimate for each RSSI value. This can be performed for the values of multiple beacons. The tag location may then be determined by multilateration.

Fig. 3 shows the distribution of measured RSSI values for 1m distance between the transmitter beacon and receiver tag.

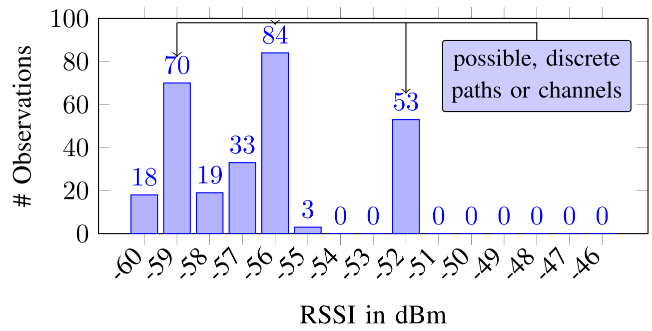

Fig. 3. Number of observations of RSSI values in 1 m distance. Due to effects like multipath fading, the distribution does not converge to a log-normal one.

The distribution does not converge to a log-normal, as would be expected, after more than 300 observations. This is caused by different attenuations and interferences on the different, used BLE-transmission channels and due to multipath interference [8]. A simple weighted centroid algorithm was proposed by Dong and Xu [21]. This approach combines the known beacon positions with the measured RSSI values to arrive at a location estimate by weighting and summing the positions.

2) Location Estimation by Fingerprinting: Besides direct inversion of a signal-strength-to-distance relationship, there exists a class of probabilistic methods. These methods seek to maximize the likelihood of a given observation belonging to a location [47]. The *posterior distribution* of the location is given by Bayes' law

$$p(l \mid o) = \frac{p(o \mid l)p(l)}{p(o)}, \tag{2}$$

where $p(l)$ is the prior distribution of the location l and $p(o \mid l)$ is the *likelihood function* of an observation o at a given location. A direct approach to estimate $p(o \mid l)$ is to build a map of the RSSI distribution in the operation environment. The map is collected by sampling a grid of K points within the desired room. In total, L beacons are used. A fingerprint matrix $\mathbf{F}$ consisting of the RSSI measurements $r_{i,j}$ (in dBm) is then built, where i is the index of the corresponding grid node and j the index of the beacon by which the signal has been transmitted.

$$\mathbf{F} = \begin{bmatrix} r_{0,0} & \dots & r_{0,L-1} \\ \vdots & \ddots & \vdots \\ r_{K-1,0} & \dots & r_{K-1,L-1} \end{bmatrix} \in \mathbb{Z}^{K \times L}. \tag{3}$$

The position estimation can be performed by a k-Nearest-Neighbor (kNN) regressor as described by algorithm 1.

A detailed overview of distance functions was given by Honkavirta *et al.* [48]. Another point to consider is the distance function subject to design that fits the dataset. In this case, the standard ℓ_2-norm was employed. Since nearly no message contains an RSSI reading of every single beacon, this has to be taken care of in the distance function, i.e., only the beacons from which a reading is present are incorporated into the distance measure. If weighted equally, the fingerprints with few RSSI entries are equally weighted as fingerprints with similar distance. This may be incorporated into the weighting function by adding a term k, which evaluates the number of compared RSSI measurements. This weighting function is then

Algorithm 1 Weighted kNN-Regression for RSSI-Based Position Estimation

Data: Fingerprint matrix $\mathbf{F} \in \mathbb{Z}^{L \times K}$, vector $\mathbf{o} \in \mathbb{Z}^K$ of observed RSSI values; Position matrix $\mathbf{P} \in \mathbb{Z}^{L \times 2}$
Result: Vector $\hat{\mathbf{p}} \in \mathbb{R}^2$ of estimated spatial position
begin
  $\hat{\mathbf{d}} = \text{distance}(\mathbf{F}, \mathbf{o})$; $\hat{\mathbf{d}} \in \mathbb{R}^L$;
  $\mathbf{u} \leftarrow \min\left(\hat{\mathbf{d}}, k\right)$ // the k smallest entries ;
  $\mathbf{w} = \text{weight}\left(\mathbf{u}, \hat{\mathbf{d}}\right)$
  $\hat{\mathbf{p}} = \mathbf{w}^T \mathbf{u}$

$$\text{weight}\left(\mathbf{u}, \hat{\mathbf{d}}\right) \triangleq \hat{\mathbf{d}}^{-1} + k \text{ for } \hat{\mathbf{d}} > \mathbf{0}, \tag{4}$$

where $\mathbf{u}$ are the selected candidates and $\hat{\mathbf{d}}$ the values of the selected distance metric, both as defined in algorithm 1.

3) Linear Constraint Estimation: Due to the high setup cost and with time increasing obsolescence of fingerprints, it is desirable to use a model that does not rely on many calibration points. Additionally in cases where a localization is performed within a corridor or similar geometry, a linear constrained may be imposed on the localization. In the fingerprinting case, this simply reduces to removing fingerprints not lying in proximity of the constraint. For methods which utilize relations like equation (1), two models are now presented.

a) Constrained Localization by Likelihood (CLL): A likelihood function is derived from a RSSI-distance model. A circular density function $\mathcal{L}(\mathbf{x})$ around each beacon, with a radius according to the measurement data, is created and summed up for every given measurement

$$\mathcal{L}(\mathbf{x}) = \sum_i \left\| \frac{\|\mathbf{x} - \mathbf{b}_i\|_2^2}{d_i^2} - 1 \right\| \tag{5}$$

$$\arg\min_{\mathbf{x}} \mathcal{L}(\mathbf{x}) \text{ s.t. } \mathbf{A}\mathbf{x} = \mathbf{b}. \tag{6}$$

where $\mathbf{b}_i \in \mathbb{R}^2$ are the beacon locations and $\mathbf{A}$ is the linear constraint matrix. This non-convex function may then be minimized on the given constraint.

b) Constraint Weighted Centroid (CWC): Another approach is to extend the WC method [21]. Prior to weighting and summing up, the beacons are projected to the nearest point on the constraint. Suppose the constraint (6) is reformulated as the parametric line function $\mathbf{g}(t) = \mathbf{m} + \mathbf{n}t$. The projected point is then given by $\mathbf{b}_i' = \mathbf{m} + \mathbf{n}\langle\mathbf{n}, \mathbf{b}_i - \mathbf{m}\rangle / \langle\mathbf{n}, \mathbf{n}\rangle$, where $\langle\cdot,\cdot\rangle$ denotes the inner product. In the next step, the weights w_i of each projected point $\mathbf{b}_i'$ and summed up to arrive at a location estimate $\hat{\mathbf{p}} = \sum w_i \mathbf{b}_i'$. Several weighting functions are given in [21], for instance a simple relative weight may be assigned proportional to the received RSSI value with $\sum w_i = 1$. One more approach is to use a distance model (e.g. (1)) and weight in the distance.

4) Discussion: The upside of multilateration is that there are usually only two parameters which have to be tuned to perform a localization. In that way, it is not necessary to map out the whole localization area with calibration points. A low installation effort follows from this circumstance. Prior information may be incorporated by constraining the localization estimation as detailed above. The caveat is although that the RSSI measurement are highly corrupted by noise, environment and multipath effects, as shown earlier. Furthermore, due to the available information, it is in general difficult to incorporate antenna isotropies in a simple way. However, PCB-antennas with high anisotropies are frequently used in such devices because of the inexpensiveness to integrate them. This leads to further restrictions on the performance. Another point is the changing environment in the deployment area, which may lead to obsolescence of fitted model parameters. Therefore, this is only a coarse approach with limited generality.

Fingerprinting on the other hand solves the problems of geometrical influences of the surroundings and anisotropies. Moreover, *a priori* information is naturally encoded by only adding fingerprints where the probability is nonzero. Still this approach requires a significant additional installation effort due to the sampling of a complete calibration point map. Also it will remain limited when it comes to changing environments, which may render the calibration map obsolete (or imprecise) over time.

B. Ultrasound Localization

In ultrasound localization, the low propagation speed $c_{\mathrm{ac}} \approx 343\,\mathrm{m\,s^{-1}}$ is exploited to reduce the instrumentation complexity when measuring time. In this work, we regard the TDOAs, which are calculated from the TOAs.

1) Time of Arrival: The propagation time $t_{\mathrm{s},i}$ between the sending time t_{s} of a moving beacon and the TOA T_i of this transmission at the ith receiver is formulated as

$$T_i = t_{\mathrm{s}} + t_{\mathrm{s},i}. \tag{7}$$

We assume the sound wave travels in a straight line, so we can reduce the distance estimation to

$$c_{\mathrm{ac}} \cdot t_{\mathrm{s},i} = \|\mathbf{M}_i - \mathbf{S}\|_2, \tag{8}$$

where $\mathbf{M}_i = [x_i, y_i]^T$ is the known ith receiver's position and $\mathbf{S} = [x, y]^T$ the position of the sender at the time of transmission.

2) Time Difference of Arrival: The sending time t_{s} of all recorded TOAs from one sender is the same. Hence, regarding the differences $\Delta T_{i,j}$ between the TOA of two different receivers (i.e., T_i and T_j) for the same transmitted signal removes the sending time from the localization problem:

$$\Delta T_{i,j} = T_i - T_j. \tag{9}$$

This leaves the speed of sound c_{ac}, the multidimensional sender position $\mathbf{S}$ and a remaining timing error $\vartheta_{i,j}$, which can be regarded as a cumulative error term, to be estimated. The resulting hyperbolic equation shown in (10) needs to be solved for the sender position for each measurement.

$$\vartheta_{i,j} = \Delta T_{i,j} - \frac{1}{c_{\mathrm{ac}}}\left(\|\mathbf{M}_i - \mathbf{S}\|_2 - \left\|\mathbf{M}_j - \mathbf{S}\right\|_2\right). \tag{10}$$

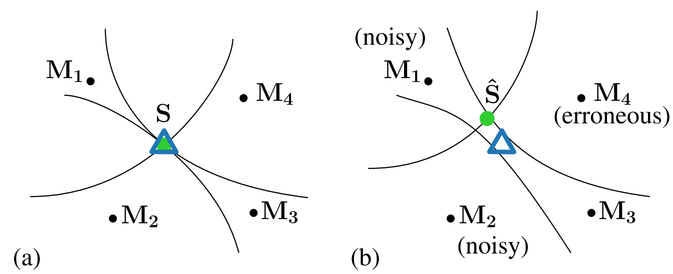

Fig. 4. Sample geometry of ultrasound localization, $\mathbf{M_n}$ are the US receivers, $\mathbf{S}$ and $\hat{\mathbf{S}}$ are the true and estimated sender locations respectively. (a) General operation of noisy-free TDOA-based positioning. (b) Estimation result of parameterization scheme using noisy and erroneous TDOA measurements.

As it is shown in Fig. 4, geometrically, each noise-free TDOA equation (10) defines a hyperbola on which the sender should lie in the two-dimensional (2-D) space. With at least two hyperbolas, the sender location is produced by intersection.

The pros and cons of TDOA-based ultrasound localization are summarized as follows.

Pros:

- With the use of (10), synchronization between the sender and receivers is not needed anymore.
- The influence of signal amplitude is limited to timestamp acquisition.

Cons:

- Sensitive to echoes from multipath propagation.
- Positions of receivers have to be known in advance.
- Change of receiver positions requires re-initialization of the system.
- Receivers still need to be synchronized.

Despite the promising achievable accuracy assured by the TDOA and acoustic metrics [5], the localization performance of such a system can still be easily degraded in the presence of adverse environmental factors (e.g., NLOS and multipath propagation) inducing biased received timestamps. The challenge is the potential deduction between NLOS errors in two paths in the construction of TDOA measurements, which in turn covers up the bias-like feature of the error. Recently, convex optimization has been successfully exploited to settle this matter [49], [50], whose theoretical feasibility and robustness have been validated through extensive numerical simulations. Nevertheless, solving the resultant convex programs usually leads to very high computational complexities, which is unacceptable in real-world industrial scenarios.

Recent efforts into expression other than the conventional Cartesian coordinates in localization have achieved promising results [51], [52], which inspire us to formulate TDOA localization under possible adverse conditions in a completely different form. In short, the idea of parameterization is conceived to reshape the relationship between the sender position and TDOA measurements, after which the optimization is carried out over the newly introduced parameters (each one being associated with a corresponding hyperbola). Thus, the problem raised is lent plain and direct geometric significance that a point on one TDOA-defined hyperbola closest to all the other hyperbolas is to be searched. Assume that we have N

spatially separated ultrasound receivers in the 2-D space. The TDOA model (10) can be rewritten as

$$\frac{\left[(x-h_{i,j})\cos(\gamma_{i,j})+(y-k_{i,j})\sin(\gamma_{i,j})\right]^2}{a_{i,j}^2} - \frac{\left[(x-h_{i,j})\sin(\gamma_{i,j})-(y-k_{i,j})\cos(\gamma_{i,j})\right]^2}{b_{i,j}^2} = 1, \quad (11)$$

if we let $h_{i,j} = \frac{x_i+x_j}{2}$, $k_{i,j} = \frac{y_i+y_j}{2}$, $a_{i,j} = \frac{(\Delta T_{i,j}-\vartheta_{i,j})c_{\mathrm{ac}}}{2}$,

$$b_{i,j} = \frac{\sqrt{(x_i-x_j)^2+(y_i-y_j)^2-(\Delta T_{i,j}-\vartheta_{i,j})^2 c_{\mathrm{ac}}^2}}{2}, \quad (12)$$

and $\gamma_{i,j} = \arctan\left(\frac{y_i-y_j}{x_i-x_j}\right)$. A popular parametric equation in $\mathbf{t} = [t_{1,2}, \ldots, t_{1,N}, t_{2,3}, \ldots, t_{N-1,N}]^T \in \mathbb{R}^{\frac{N(N-1)}{2}}$ for describing (11) is

$$\begin{aligned} x(t_{i,j}) &= \pm a_{i,j}\cosh(t_{i,j})\cos(\gamma_{i,j}) \\ &\quad + b_{i,j}\sinh(t_{i,j})\sin(\gamma_{i,j}) + h_{i,j}, \\ y(t_{i,j}) &= \pm a_{i,j}\cosh(t_{i,j})\sin(\gamma_{i,j}) \\ &\quad - b_{i,j}\sinh(t_{i,j})\cos(\gamma_{i,j}) + k_{i,j}. \end{aligned} \quad (13)$$

Replacing $\Delta T_{i,j} - \vartheta_{i,j}$ by the available $\Delta T_{i,j}$ and based on (13), we propose to solve the following minimization problem:

$$\hat{\mathbf{t}} = \arg\min_{\mathbf{t}} \sum_{m=1}^{\frac{N(N-1)}{2}-1} \sum_{l=m+1}^{\frac{N(N-1)}{2}} \left\| \begin{bmatrix} x([\mathbf{t}]_m) \\ y([\mathbf{t}]_m) \end{bmatrix} - \begin{bmatrix} x([\mathbf{t}]_l) \\ y([\mathbf{t}]_l) \end{bmatrix} \right\|_2^2, \quad (14)$$

which aims at finding a set of points on the TDOA-defined hyperbolas with each one of them having the minimum Euclidean distances (in the nonlinear LS sense) to others. Note that $[\mathbf{t}]_{\mathrm{m}}$ represents the mth element of vector $\mathbf{t}$. It is seen that (14) falls into the category of nonlinear LS problems, for which mature optimization solvers are plentifully available. Once we have obtained $\hat{\mathbf{t}}$ from (14), a simple selection scheme applying the similar LS cost function is then utilized to produce the final estimate of the sender position as $\hat{\mathbf{S}} = \left[x\left(\left[\hat{\mathbf{t}}\right]_{\hat{m}}\right), y\left(\left[\hat{\mathbf{t}}\right]_{\hat{m}}\right)\right]^T$, where

$$\hat{m} = \arg\min_{m} \sum_{\{l|1\le l\le N(N-1)/2, l\ne m\}} \left\| \begin{bmatrix} x(\left[\hat{\mathbf{t}}\right]_m) \\ y(\left[\hat{\mathbf{t}}\right]_m) \end{bmatrix} - \begin{bmatrix} x(\left[\hat{\mathbf{t}}\right]_l) \\ y(\left[\hat{\mathbf{t}}\right]_l) \end{bmatrix} \right\|_2^2. \quad (15)$$

For illustrative purposes, the procedure of TDOA-based parameterized localization is summarized in Algorithm 2 and a sample geometry with $N = 4$ is depicted in Fig. 4(b). It is observed that the erroneous and noisy timestamps collected at the corresponding receivers (due to disturbances and possible NLOS propagation conditions) might result in heavily stretched hyperbolas, which no longer intersect at an exact point can in turn greatly deteriorate the localization performance. Nonetheless, our parameterization scheme is still capable of yielding reliable sender location estimates.

Algorithm 2 TDOA-Based Parameterized LS Position Estimation

Data: TDOA measurements $\{\Delta T_{\mathrm{i,j}}\}$, vector $\mathbf{o} \in \mathbb{Z}^K$ of observed RSSI values, and receiver positions $\{\mathbf{M}_{\mathrm{i}}\}$.
Result: Vector $\hat{\mathbf{S}} \in \mathbb{R}^2$ of estimated sender position.
begin
(i) Solve (14) with additional NLOS error mitigation constraints (16)–(18) for fusion being considered;
(ii) Perform data selection according to (15).

V. Fusion

When having the time difference of arrival of two receivers, the possible locations of the sender lie in a hyperbola (10). Under ideal circumstances, one would estimate the position of the sender by locating the intersection of multiple hyperbolas in the 2-D space. However, in certain occasions, LOS signals are blocked and only NLOS signals are received. Moreover, the sender can be at a large distance from the receivers such that its signals can only reach a limited number of receivers. One could place a large number of receivers, but this would increase the cost of the system.

Due to the high precision of the acoustic measurements compared to the RSSI measurements, it is convenient to estimate the position of the target using the acoustic measurements when they are available. However, at certain occasions only two or three LOS acoustic measurements are available. In these cases, one can make use of the RSSI measurements to choose the most likely TDOA solution. Moreover, one can also use the RSSI measurements to discard NLOS measurements, which would lead to unfeasible estimations. In order to do this, we propose to take advantage of the TDOA information to estimate a position, which is constrained by the RSSI measurements.

Then, we minimize (14) and (15) with the constraint

$$\left\|\hat{\mathbf{S}} - \mathbf{b}_i\right\|_2 \le d_{\max,i} \quad \forall i \in [0, \cdots L], \quad (16)$$

where $\mathbf{b}_i$ are the beacon positions and $d_{\max,i}$ is defined by the received signal strength RSSI_i as

$$d_{\max,i} = 10^{\frac{(\mathrm{MAXRSSI}-\mathrm{RSSI}_i)}{(10\gamma)}}. \quad (17)$$

The value of MAXRSSI is the maximum received signal strength at 1 m in LOS. In doing so, $d_{\max,i}$ will provide us with a higher bound for the distance to the beacon, as the distance to it can never be higher than $d_{\max,i}$. In other words, an RSSI means that either the target is at a distance $d_{\max,i}$ in ideal conditions or the signal has been attenuated, in such case the target will be closer to the beacon. The NLOS noise of the received timestamps must be also positive, i.e.,

$$T_i \ge t_{\mathrm{s}} + t_{\mathrm{s},i} + \epsilon_i, \quad (18)$$

where ϵ_i accounts for the LOS noise, which is assumed to be limited.

Imposing these constraints over the parametrized hyperbolas mentioned in the previous section results in the estimated position of the target.

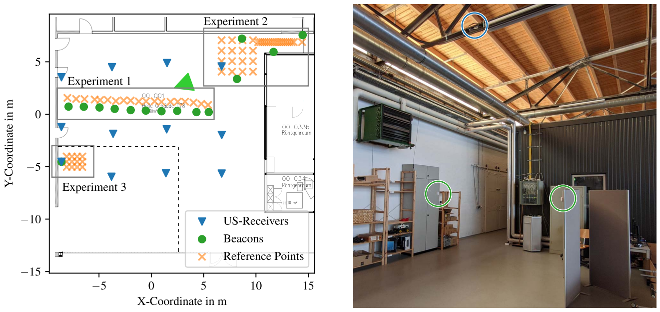

Fig. 5. *Left:* Experiments Overview. The first experiment is concerned with estimating the performance of linear constrained localization with BLE, whereas the second demonstrates the efficacy of using BLE data to directly enhance the TDOA solution. The point of view of the right figure is marked with the green triangle. *Right:* View of the second experiment. The US-receiver (blue) is mounted at a height of 4.8 m. The two foremost Bluetooth beacons (green) are visible, which are installed at a height of 1.6 m. The left figure shows the corresponding point of view.

We also eliminate the TDOA measurements which do not fulfill:

$$| \Delta T_{i,j} | - \xi \leq \frac{1}{c_{\mathrm{ac}}} \left(\left\| \mathbf{M}_i - \mathbf{M}_j \right\|_2 \right), \tag{19}$$

where ξ is set depending on the measurement noise distribution.

VI. Evaluation

The Bluetooth and ultrasound localization experiments were conducted using *Minew E2 Max Beacons* and the ASSIST system [12], respectively. The cost of the Bluetooth devices lie in the order of tenths of euros, whereas the US system in several hundredths per receiver (without installation). Note that the latter is an acoustic indoor TDOA target localization system based on the high pitched chirp signals and several Wi-Fi-connected US-receivers. Unless stated otherwise, the transmission power for the Bluetooth system was set to 4 dBm. The Bluetooth connection on the tag was handled by a *Silicon Labs BGM121* Module. The error is measured as root mean square (RMSE).

A. Exp. 1: Measurements of 1-D-BLE-Localization

To determine to general localization accuracy in a linear constraint BLE localization setup, an experiment was conducted, where a number of 10 beacons were placed on a line on the floor 1.5 m apart (see Fig. 5). Around 10 k RSSI measurements at 19 different points have been taken at a distance of around 1 m to the beacons and at a height of 0.3 m. The positions of both beacons and RSSI measurements were localized by the ultrasonic localization system, which has good coverage in that area. This dataset was split equally in a training and test set (position-wise), to provide a calibration map for the fingerprinting (FP) method (CLL and CWC do not need a training set, if parameters are assumed). The evaluation was then done on the test set for all methods. For the CLL and CWC methods, we assumed a path loss of $n = 2.0$ and a calibration RSSI of $\mathrm{RSSI}_{\mathrm{d0}} = -50$ dBm were assumed. A higher path-loss as well as the lower calibration signal strength level assumption is explained by the geometry of the setup: the beacons lie flat on the ground, and the measurements were taken to the right in which direction the antenna attenuation was lower. Measurements lower than −65 dBm were discarded. Fig. 6 demonstrates the performance of the proposed methods. While the fingerprinting method achieves the lowest errors in most cases, in settings with several beacons at hand, the direct methods are on-par. As expected, the error increases as the number of beacons decreases. With a higher number of averaged messages K_{avg}, the error may still be reduced. The degradation acts on all methods roughly equally. In the error sense, the fingerprinting is slightly ahead in low averaging settings with few beacons as well as the high averaging when many beacons are available. On the other hand, with low averaging and few beacons, there is not much accuracy improvement of the CLL or CWC method over random guessing. Table III provides an overview of some key error metrics of different methods.

TABLE III
Error Metrics for 1D-BLE-Localization With $K_{avg} = 2$

# Beacons	Method	Median in m	95% CI in m
10	FP	0.80	4.66
	CLL	0.90	5.53
	CWC	1.01	5.32
5	FP	2.39	7.79
	CLL	1.84	6.25
	CWC	1.79	6.02
2	FP	2.49	7.39
	CLL	2.22	8.56
	CWC	2.97	8.92

TABLE IV
Error Metrics for US/BT-Fused Localization

BT	Min. # Hyp.	Median in m	95% CI in m
•	2	0.58	5.62
	2	0.69	7.55
•	3	0.48	4.66
	3	0.53	5.72
•	4	0.38	2.96
	4	0.44	5.54

B. Exp. 2: Data Fusion

In order to test if the RSSI measurements can improve the estimation results using only ultrasound timestamps, we performed an experiment where we set a total of 4 beacons and 12 US-receivers. The target is located in 35 different static positions. The beacons and the target positions are placed in areas which are poorly covered by the US-receivers (see Fig. 5). A path loss of $n = 1.6$ and $\mathrm{RSSI}_{\mathrm{d0}} = -26$ dBm was assumed in this scenario.

In Fig. 7 (left), one can observe the empirical cumulative distribution of the error in cases with different number of required intersecting hyperbolas. The result shows how using RSSI measurements reduce the large errors caused by NLOS

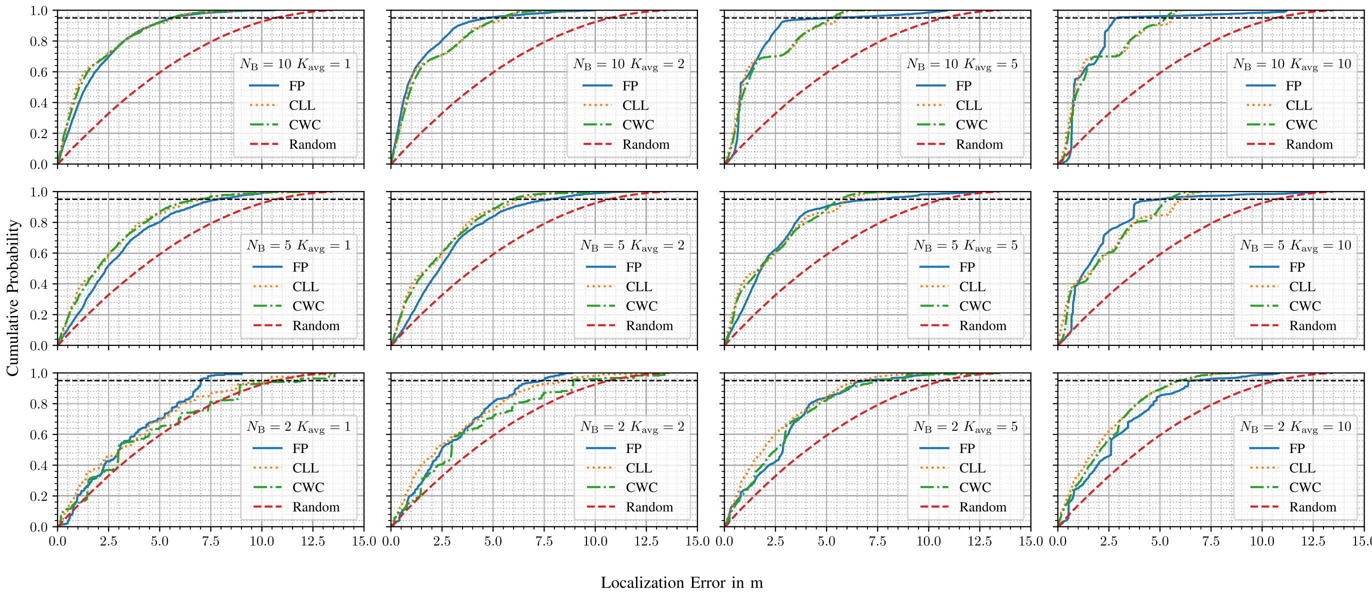

Fig. 6. Empirical cumulative distribution (ordinate) of the localization error (RMSE) in meters (abscissa) under different numbers of beacons N_B and RSSI measurements averaging factors K_{avg}. The 95% error margin is marked by the dashed line. The last column was measured using only the two outmost beacons. Under this condition, performance improvement over random guessing can hardly be achieved. With a higher count of averaged messages K_{avg}, a higher accuracy can still be obtained. For a higher number of beacons, these methods are on-par.

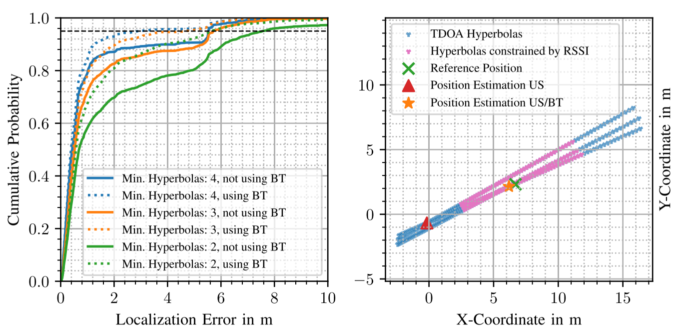

Fig. 7. *Left:* Empirical cumulative distribution of the localization error (RMSE) achieved by the presented data fusion approach with different minimum number of intersecting TDOA hyperbolas. One can observe how constraining the solution space with the RSSI measurements reduces the error caused by NLOS measurements. *Right:* Constraining the solution space with RSSI measurements, one can reduce the ambiguity caused by NLOS measurements. In this experiment, one can observe how the TDOA hyperbolas generated by the ultrasound measurements have two intersection points due to NLOS measurements. The crossing point corresponding to that produced from the LOS measurements is correctly chosen with the help of the Bluetooth (BT) measurements.

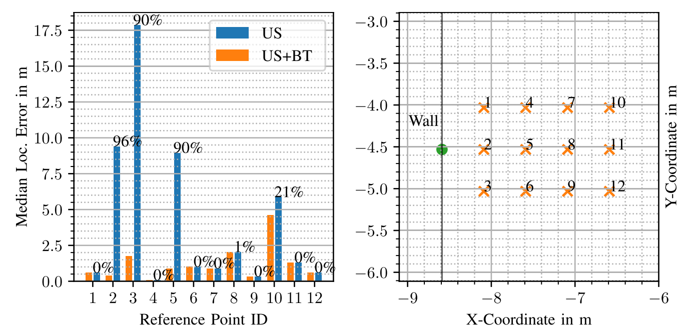

Fig. 8. *Left:* Median localization error in meters of the third experiment with error reduction in percentage. *Right:* IDs of the reference points in this experiment, with the beacon on left (green dot). In closer proximity to the beacon, the localization error may be minimized significantly.

measurements. An example of this is shown in Fig. 7 (right), where the Bluetooth measurements constrain the solution space and remove the ambiguity caused by the NLOS measurements. Table IV tabulates the corresponding error metrics.

C. Exp. 3: Error Mitigation

In this experiment, one beacon is fixed to a wall. The ultrasonic localization system is prone to multipath errors, which are usually introduced by concrete surface (like e.g. walls, tables or the floor). This multipath influence can lead to great localization errors. The RSSI signal of the beacon is used to enhance the localization accuracy of the overall system. Figure 8 shows the median localization error and the corresponding reference point map. Generally the multipath influence increases with the proximity to the wall up onto a certain point where the phase difference is at a maximum, until it decreases again. In the figure, the US error closer to the wall is overall greater than farther away. The US positions were estimated with two hyperbolas 40.9% of the time, 58.7% with three and 0.36% with four. This is an indicator of the limited number of line-of-sight signals received in such positions. In areas with high multipath influence the algorithm is able to significantly reduce (e.g. median error of 27.84 m US vs. 0.39 m US+BT in reference point 2) the localization error in respect to only using the ultrasonic signal.

VII. Conclusion

We have shown possibilities to fuse the BLE data with those from an ultrasonic system. It was possible to show, that the novel, proposed method, using BLE data to constrain the TDOA hyperbolas could improve the overall accuracy. In areas of low discriminability of ultrasonic measurements, the addition of smartly placed Bluetooth beacons can offer advancement to the localization accuracy. This concerns mostly areas outside the direct coverage area of the ultrasonic systems. Usually, ultrasonic systems are deployed in areas where 2-D localization is desirable. Deployed in areas where only 1-D localization is necessary (like corridors), the ultrasonic approach might be uneconomical due to the high installation effort. Adding Bluetooth beacons can serve as a simple extension to the coverage area of a localization system. For this use case, we proposed linear constrained localization methods and have demonstrated that the CWC method will be preferable if the effort of building up a map of fingerprints should be spared. In the future work, we will further investigate measures and fusion algorithms of how the hand-over between the two overlapping regions can be optimally handled based upon the achievable accuracy. Furthermore, the usage of microphone arrays in this scenario will pose interesting questions on how accurate localization can be performed with distorted ultrasonic data augmented by the Bluetooth counterpart. With the upcoming relevance of UWB in the area of indoor localization, an additional concern will be investigating under which circumstances UWB fails and how this can be mitigated by complementary measures.

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