Enabling Indoor Object Localization through Bluetooth Beacons on the RADIO Robot Platform

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***Abstract*— Localization is one of the four pillars of the autonomous robotic control loop. In order to work in complete unknown indoor environments, the robot needs to map its surroundings. This is done via the simultaneous localization and mapping (SLAM) algorithm. However, the SLAM algorithm does not provide additional context to the generated map. If this information is required, it needs to be provided by the operator. With Bluetooth Low Energy (BLE) technology, position dependent information can be annotated to the generated map without operator input. BLE beacons need to be positioned at points of interest for the robot and then need to be localized. Because the BLE beacon broadcasts an ID, localization is based on the Received Signal Strength Indication (RSSI). This paper presents an approach to localize BLE beacons in the RADIO indoor environment. The robot has one BLE receiver which must be used cleverly in order to triangulate the BLE beacons position.**

Keywords*— *RADIO, Turtlebot, ROS, Bluetooth Beacons, BLE, Localization, Mapping, SLAM, Robotics

I. Introduction

Several applications of the daily living use information about their spatial position to enable advanced features and to improve the life of the user. Smartphone applications and navigation systems are only two examples. Both are usually based on the *Global Positioning System* (GPS) or the Russian *Globalnaja nawigazionnaja sputnikowaja Sistema* (GLONASS). A drawback of these systems is the limited connectivity within buildings, as the signal strength is often not high enough to provide the required functionality.

For indoor localization, a more reliable approach is required that can also work in short range scenarios. GPS and GLONASS are hereby stretched to their limits.

The context of this paper targets the localization of objects within a building and uses a reverse methodology. Instead of using at least three transmitters, as e.g. required for GPS, only one sender is connected to at least three receivers.

Objects can therefore be equipped with a transmitter, enabling stationary receivers to locate the respective device, based on signal strengths.

The *Bluetooth Low Energy* (BLE) technology avails itself for the purpose of indoor positioning, as it is robust and energy efficient. Especially the latter is important for battery-driven applications, as they last long without the need for exchanging or charging the battery.

So called *BLE Beacons* are integrated to the devices, making them smart and addressable.

The open-source software framework *Robot Operating System* (ROS) is used to integrate the BLE Beacons to the context of RADIO. RADIO, as short for *Robots in Assisted Living Environments: Unobtrusive, Efficient, Reliable and Modular Solutions for Idependent Aging* [1], targets the support and monitoring of elderly in their homely environment. Within ROS, the communication between the receivers is enabled in a distributed manner. Different instances of ROS can be started on different compute nodes with the target to cover the indoor location efficiently and to provide access to the Beacon information at any place. Hence, the approach provides a universal software framework that is scalable and allows the integration of further BLE devices to increase the resolution of the position information.

Another advantage is given by using ROS as a common basis for both, the RADIO robot platform and the indoor positioning system. The computational overhead that is induced by translating between different communication protocols is reduced to a minimum, making the entire communication more efficient.

The remainder of the paper is organized as follows: Section II depicts related work of ambient assisted living environments and the required wireless sensor networks. In Section III, the radio environment is explained. While Section IV introduces bluetooth low energy (BLE) technology, Section V shows the methods and challenges when using the BLE technology for localization. Finally, we conclude this paper in Section VI.

II. Related Work

Care delivery often comes without the use of technology. According to [2], user acceptance is the reason for this issue in 37% of the cases. The development of smart home systems is affected by obtrusiveness, which is one of its major obstacles [3]. *Activities of the daily living* (ADL) can be collected and analyzed by smart homes or similar sensor networks. These networks typically act as assistive environments and telemedical systems and can be used to recognize the emotional status of patients and the identification of emergency situations, such as the detection of falls. Sensors should be placed in a mask disposal to achieve the required level of unobtrusiveness. Furthermore, no physical contact to the patient should be allowed. Hence, monitoring of health needs to be done remotely. Technical and user-related advantages must be considered to face several shortcomings, such as the placement of sensors. Sensors must be placed in a way that is both discrete and useful, which is not straightforward.

Specialized personnel are often required to install the devices, when an understanding of the involved audio-visual analysis technologies is needed to identify advantageous positions in each user's home. Even if sensors could be positioned in an optimal way for the analysis tools, they may have a limited degree of freedom or are completely stationary. Even if cost and complexity play a subordinate role, simply installing multiple sensors is not going to overcome the restrictions on angles and distances. Using multimodal sensor data to recognize ADL and mood related events in an unobtrusive manner is a rather challenging task under any circumstances. Data is often noisy and has a low quality, when masked sensors are used. The interclass similarity is another challenging issue. Interclass similarity denotes the similar characteristics of sensor data. A complex task for example is the technical identification of differences between related activities such as drinking coffee or water. Moreover, the null class problem, which means that irrelevant data is present, further challenges this topic. Finally, class imbalance affects the recognition of ADL, i.e. when events occur infrequently. Also the volume and diversity of activities are of concern.

Different ADL can be monitored based on several types of sensors. Dressing activity failures were monitored by Matic et al. [4]. They used both radio frequency identification (RFID) tracking and computer vision. Matic et al. monitored failures that can occur when changing clothes. This includes putting clothes on in the wrong order, backwards or other way around or only partially and at a wrong part of the body. Also the number of layers in relation to the current temperature is put under observation. Dressing steps can be observed using RFID tags and a Bayesian model. The RFID tags had been embedded in clothes. Simple dressing events were inferred by a clustering scheme that finally fuses the results. The detection of clothes changing is also investigated by Sgouropoulos et al. [5]. They use a Kinect Sensor to detect the change of particular clothing based on depth and RGB (*Red-Green-Blue*) information.

RFIDs are also used by Philipose et al. [6]. Wireless gloves enable the detection of nine ADL including oral hygiene, toileting, washing and personal appearance. The Fusion of RFID information and visual properties has also been addressed. Sparse and noisy RFID readings combined with common-sense knowledge and visual features are used by Wu et al. [7] to automatically learning object models from video.

Cook et al. [8] used various sensors for monitoring motion, temperature, water and stove burner use to observe five basic ADL activities: the telephone and medication use, hand washing, meal preparation, as well as eating and cleaning. Naive Bayes classifiers and Markov models were applied to recognize the aforementioned activities.

The system of Mihailidis et al. [9] uses visual features and custom logic rules in order to recognize steps in hand washing. Fleury et al. [10] recognized ADLs including hygiene and dressing by successfully fusing several sensors with a *Support Vector Machine* (SVM) classification scheme. Several ADLs were detected by Dalton et al. [11] using wearable wireless accelerometers. The detection of potentially dangerous activities for elderly people is investigated by Zhang et al. [12]. They use an RGB-camera along with several ADLs and extract kinematic features by tracking joints on the human body. The latter is enabled by the Microsoft Kinect *Application Programming Interface* (API). Several one-vs-all SVM classifiers are used for the recognition of simple activities. For finer activities, such as ADLs, Zhang et al. adopt a bag-of-motion-features approach before applying SVM classifiers. In the context of specific ADLs related to eating and drinking, the Kinect Sensor is also used by Hondori et al. [13] in order to monitor intake gestures.

The recognition of bathroom activities, such as bathing, toilet use and personal hygiene ADLs is mainly based on sound analysis [13]. Also, the detection of sounds relevant to general events including doorbell, phone ring and speech was investigated by the USEFIL project, based on acoustic information. Baseline audio analysis approaches to detect ADL-specific audio events, such as dish washing and step sounds, were adopted by Vacher et al [14]. Audio information can be rather useful when recognizing emotions from speech [15]. Most of the face recognition studies focus on combining information from visual-based facial expression analysis, as the analysis of the human face is important for emotion expression and perception [16].

III. RADIO ENVIRONMENT

The technology developed within the RADIO project targets the domestic homes of elderly people. But these homes normally do not provide infrastructure for ad-hoc ambient assisted living services. The infrastructure connecting all hardware and software components is provided by RADIO, focusing on the unobtrusiveness of the required components. The RADIO architecture consists of the smart home services and the *Internet-of-Things* (IoT) platform, as seen in Figure 1. The latter is located in the cloud and can be used to control the smart home functionality and access relevant data. Different tasks are fulfilled by several subgroups of the smart home environment. The basic smart home functionality is handled by the first subgroup. In the second subgroup, all kinds of devices which communicate via Bluetooth are present. They can be read for data analysis purposes. The subgroup is described in Figure 1 as “BT devices”. The last subgroup represents the functionality of the mobile robot platform. The user benefits from services provided by the robot. Furthermore, health data is collected for monitoring purposes. Internet connectivity is not required for providing the intended smart home functionality. This means that the user does not notice a difference between a connected and a standalone smart home. Sensor and actuator devices consist of *commercials-off-the-shelf* (COTS) components such as Z-Wave products (Figure 1). This helps to ensure long term support and reliability. Z-Wave is designed for close range sensor and actuator networks based on a wireless communication protocol. Here, no coordinator node is required as Z-Wave automatically initializes a full mesh network [17]. Hence, it is possible to modularize the architecture and add additional sensors if required. The sensor data can be used to recognize daily activities and routines besides the basic smart home services. This information can also be used to draw inferences about the user’s health. The integration of a mobile robot platform to the smart home environment is another challenge of the RADIO project.

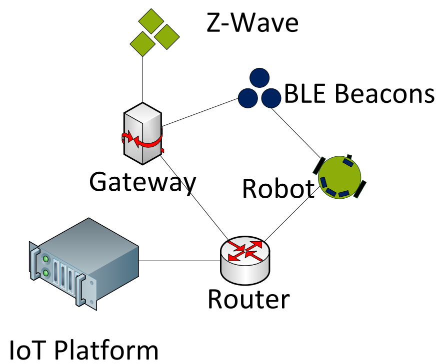

Figure 1: RADIO architecture with IoT platform, robot platform, and wireless sensor infrastructure

A typical *Ambient Assisted Living* (AAL) environment effectively consists of nodes integrated in a home environment. Those nodes can be integrated in several devices or worn by the user, if they are small and ideally inexpensive. Furthermore they should be able to support non-specific applications and offer sufficient levels of security. Robots represent an integral part of this constellation of wirelessly communicating nodes. While actively interacting with the rest of the nodes, the presence of the robot is known by the user. The robot can therefore be used to communicate with the user.

IV. Bluetooth Low Energy

Consequently, in the context of RADIO the wireless communication technologies are of paramount importance. In that respect RADIO aims to heavily invest on the BLE communication protocol as a prominent technology for future wireless sensor networks and cyber physical systems. On one hand, BLE is going to be explored as a solution most fitting the RADIO requirements. However research effort is needed to enhance and advance BLE in order to address important shortcomings posed by RADIO objectives. BLE is usually presented as a smaller, highly optimized version of its bigger brother, classic Bluetooth. However, BLE has different design goals and different approaches in various aspects. In particular, the focus was to design a radio standard with the lowest possible power consumption optimized for low cost, low bandwidth, low power, and low complexity.

BLE is an extension of the classical Bluetooth technology. It has reduced energy consumption and size and can be produced at lower costs. BLE allows sending small impulses over long distances.

Within the scope of Bluetooth 4.0, it was developed by the Bluetooth Special Interest Group in 2010. BLE hereby exists besides the classical Bluetooth standard [18]. Its main advantage is the low energy consumption with currents of 12 µA on average. Max. 12.5 mA are needed for a connection interval of one second [19]. Small batteries can therefore be used to drive the BLE transmitter and to enable connections with up to 50 m in distance.

Figure 2 presents the four different modes of the BLE connection. The unconnected mode is separated into Broadcaster and Observer. In connected mode, the device can be a peripheral or a central.

One of the modes is assigned to the BLE device during the boot process. The device remains in this mode at least for one connection period.

The BLE modes can be separated in a sending and a receiving mode, independently from the connection type. In the following, they are described in detail.

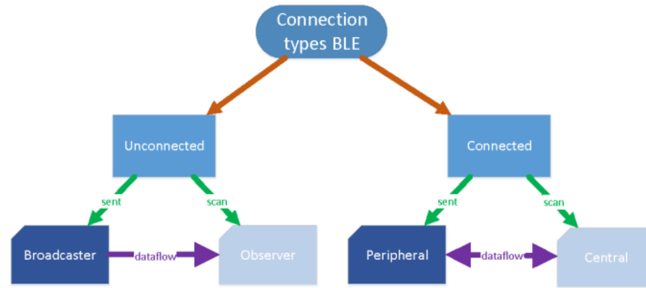

Figure 2: BLE connection types

Broadcaster: Periodically sends advertising packets with up to 31 Byte of data.

Observer: Searches for broadcasters and receives their advertising packets via one of three advertising channels.

Peripheral: Periodically sends connectable-advertising-packets to allow a master to establish a connection. The peripheral itself acts as a slave.

Central: Periodically searches on the advertising channels for connectable-advertising-packets of a peripheral. It tries to initiate a connection with the peripheral. Central hereby acts as master.

Devices can be identified using the advertising packets, sent over advertising channels. These packets can be sent in broadcaster or in peripheral mode. They can be received in observer and central afterwards.

Central usually acts as data-processing device, e.g. a robot or a smartphone, which requests data from a peripheral, e.g. a heart rate monitor or a smartwatch. The peripheral is an independent device and provides data of internal sensors to the central. This is done using a bidirectional connection.

Due to low production costs, small sizes and high operating time, BLE devices can be integrated in nearly every platform [19].

V. Localization Methods

Because bluetooth beacons only broadcast their ID, the *Received Signal Strength Indication* (RSSI) is used in order to extract position information out of the beacons signal. The RSSI value can then be converted into a distance measurement. With one beacon, a distance measurement can only define a region of interest in which the receiver is currently located. The BLE receiver can extract a distance to the BLE beacons by solving the free space loss equation. Generally the free space loss of a signal is described by

$$F = \frac{P_{Rx}}{P_{Tx}} = \left(\frac{\lambda}{4 \cdot \pi \cdot r}\right)^2, \text{ with } \lambda = \frac{c}{f}. \quad (1)$$

P_{Rx} describes the signal power received by the receiver and P_{Tx} describes the signal power sent by the sender. r represents the distance between sender and receiver and f is the signals frequency which is 2.4 GHz for Bluetooth. According to equation (1), the received signal strength is reduced by $\sim \frac{1}{r^2}$ with increasing distance from the sender. However, indoor environments vary greatly in terms of floor plan and equipment, thus influencing the signal strength through signal reflection, refraction, or interference with other signals. In order to incorporate these factors into the distance measurement, a logarithmic distance loss model is used. This model adds the variable γ which describes the signal loss in dependence on the surroundings [20].

$$\frac{P_{Rx}}{dBm} = \frac{P_0}{dBm} - 10 \cdot \gamma \cdot \log_{10}\left(\frac{r}{r_0}\right), \text{ with } \gamma \in R \tag{2}$$

Here, P_0 describes the received signal strength to the corresponding distance r_0. The value for γ is determined through several test measurements with known distances. However, when using equation (2) for distance calculation, the resulting distances are very noisy and inaccurate. Therefore, converting the RSSI values into distances requires exhaustive measurements in the respective indoor environment because the absorption of the signal varies greatly depending on the surroundings.

Thus, we have to approximate the relation between RSSI values and the corresponding distance for our specific environment. Because the relation of RSSI to distance is dependent on the surroundings, we performed measurements in a hallway which is 2m wide and 50m long and in a room with $4m \times 5m$ floor space. Figure 3 shows the relation of RSSI and distance and the corresponding floorplan of the hallway.

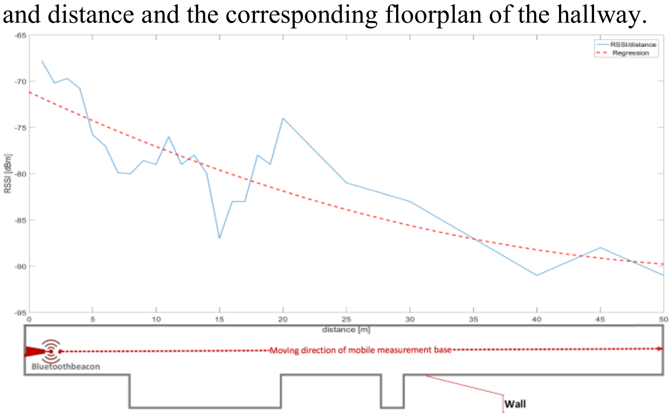

Figure 3 RSSI to distance relation of in the hallway

A beacon was positioned at the start of the hallway in 1.5m height; see Figure 3 the Bluetooth beacon icon on the left. Starting from the beacons position, signal strength measurements are conducted in 1 meter intervals until the end of the hallway is reached. At every measurement position, 40 individual measurements were executed and the mean value was calculated. All measured mean RSSI values are shown by the solid line in Figure 3. Between 8m and 20m, a larger width of the hallway can be seen. In this region, the RSSI values do not correlate well to their respective distance. We can see a decrease of the received signal power from -79dBm to -87dBm. This occurrence leads to the assumption that in this region more reflections and refractions influence the signal strength. In the region after 20m distance, the signal power increases again to -73dBm. As can be seen, no direct relation between the RSSI values and the corresponding distance can be established. The RSSI values do not even decrease monotonously with increasing distance. Therefore, we determine a regression function which fits the measurements in a satisfactory manner. The regression function is depicted in equation (3)

$$r(x_{rssi}) = 0.07472 \cdot x_{rssi}^2 + 10.106 \cdot x_{rssi} + 345.21 \,. \tag{3}$$

The measurements in the second room with a size of $4m \times 5m$ show a different behavior of the signal strength in relation to the respective distance. Figure 4 shows the RSSI to distance relation of the $4m \times 5m$ room.

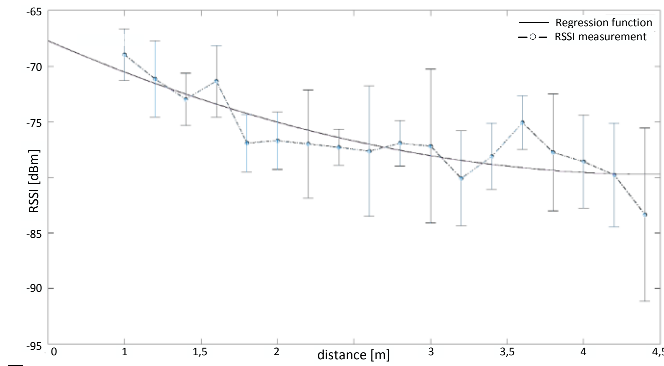

Figure 4: RSSI to distance relation of the *4m* x *5m* room

For each position, 200 measurements were performed. The deviation of an individual measurement can be up to 11% from the mean value over all 200 measurements. The standard deviation of the respective measurement point is depicted in Figure 4 as bar plot. The regression function which fits the measurements best is shown in equation (4).

$$r(x_{rssi}) = 0.0010332 \cdot x_{rssi}^3 0.24022 \cdot x_{rssi}^2 + 18.32 \cdot x_{rssi} + 460.89 \tag{4}$$

With no further information, the distance r describes a sphere in 3D space, see equation (5).

$$(x - x_m)^2 + (y - y_m)^2 + (z - z_m)^2 = r^2 \,, \tag{5}$$

with $(x_m, y_m z_m)$ being the BLE receivers position. This 3D problem can be reduced to a 2D problem, by assuming that the height z_B of the beacons is known. Thus, the sphere can be reduced to a circle. The circle has the center at $(x_m, y_m z_B)$ and the resulting radius can be calculated as

$$r_C = \sqrt{r^2 - (z_m - z_B)^2} \,. \tag{6}$$

Thus we can describe every possible position of a BLE beacon through

$$\begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} x_m + r_C \cos\varphi \\ y_m + r_C \cos\varphi \end{bmatrix} \text{ with } 0 \le \varphi \le 2\pi \,. \tag{7}$$

Through thresholding of the beacons measured distance, simple annotation of regions within an indoor environment is possible. This approach is shown in Figure 5.

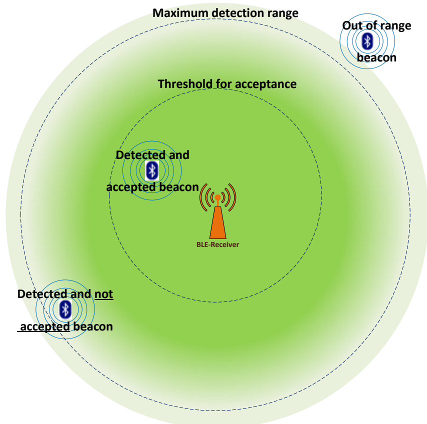

Figure 5: Thresholding of range determined through the RSSI values of BLE beacons

The main problem with this approach is that the RSSI values are very noisy. Because of the RSSIs noisy properties, a single RSSI measurement does not yield accurate and therefore valuable information. Therefore, some manner of prefiltering has to be executed before the distance conversion. As a prefilter, we use a 10[th] order *Finite Impulse Response* (FIR) filter. The FIR filter equation is shown in equation (8).

$$y_n = \frac{1}{a_0}\left\{\sum_{k=0}^{N} b_k \cdot x_{n-k}\right\} \tag{8}$$

a_0 and b_k describe the filter coefficients and were determined with the help of the *Filter Design & Analysis Tool* of *Matlab*. The filter coefficients are depicted in TABLE I. .

TABLE I. FIR FILTER COEFFICIENTS

Filter coefficients	Value	Filter coefficients	Value
a_0	1	b_5	0.3071
b_0	-0.0349	b_6	0.2562
b_1	-0.0370	b_7	0.1368
b_2	0.0209	b_8	0.02092
b_3	0.1368	b_9	-0.0370
b_4	0.2562	b_{10}	-0.0349

To show the increase in accuracy through the above filter, we compare the raw RSSI measurements with the filtered RSSI measurements. A beacon is positioned with 1.2m distance to the BLE receiver. Figure 6 shows the different results of raw RSSI and filtered RSSI measurements.

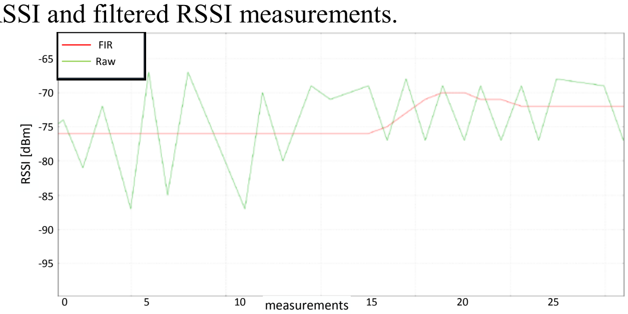

Figure 6 Comparison of raw RSSI data and FIR filtered RSSI data

It can be clearly seen that the filtered RSSI measurements are more stable than the raw RSSI measurements. To further evaluate the performance of the filtered RSSI measurement approach, we perform RSSI measurements in a radius of 1.2 m distance of the BLE beacon, see Figure 7. 150 measurements were taken on the circle in order to examine the behavior of the RSSI values when the transceiver has the same distance to the BLE beacon but a different orientation.

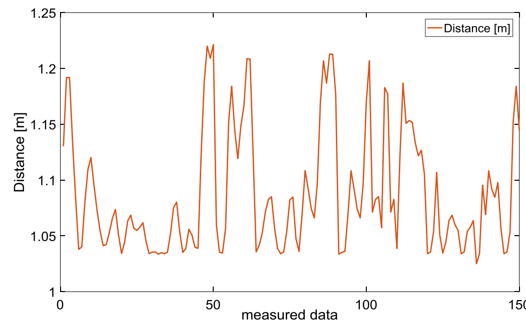

Figure 7: Calculated distance out of filtered RSSI measurements. 150 measurements were performed in a circle with 1.2m radius distance to the BLE beacon.

When calculating the distance out of the filtered RSSI values with equation (4), the mean value for the calculated distance is approximately 1.1m with a standard deviation of 0.054m. This results in a nominal error to the true distance of 10cm or 8.3%. Since the uncertainty of the calculated distances is in the range of single digit centimeters, accurate positon estimation with several RSSI measurements can be performed. For accurate position estimation through trilateration, three measurements at different positions have to be performed. Each position generates a circle with a certain radius which describes the measured distance to the BLE beacon. In the case of three measurement positions, 27 circle constellations exist. These 27 constellations contain redundant constellations which do not need to be analyzed separately. Then, these 27 constellations can be reduced to 10 different circle arrangements. We assume that no circle is contained within another circle except if several measurement errors occur. Therefore, we discard the circle arrangements where circles are included in other circles. Then, we receive four valid arrangements as seen in Figure 8. They are used to determine the *Region Of Interest* (ROI) with the help of multi lateration [16]. In the first arrangement, each circle has no intersection with the other circles. In this case, the center of the shortest connection for every circle pair is determined. These three calculated points are the triangle out of which the position estimation can be calculated for the BLE beacon. The region of interest is the circumcircle of the triangle with the radius being the uncertainty of the measurement. In the second arrangement, exactly two circles intersect with each other. Then two intersection points exist. One of the intersection points has a larger distance to the third circle than the other intersection point. The intersection point with the larger distance is discarded and the resulting region of interest is a circle with the center point being the center of the shortest connection between the remaining intersection point and the third circle while the radius of the circle and thus the uncertainty is half the length of the connection. In the third arrangement, one circle serves as connector to the two other circles. The two other circles do not share any intersection while the circle in the middle has two intersections with the respective circle. In order to determine the region of interest, all intersection points have to be calculated and the four distances between the intersection point pairs from the different circles have to be determined. The intersection point pair with the smallest distance is chosen and the center of this connection is the center point of the region of interest circle with the radius being half the length of the connection.

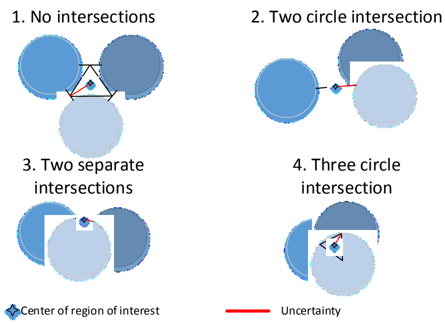

Figure 8: Four possible circle arrangements

In the fourth arrangement, all circles intersect with each other. The distance to the remaining circle is calculated for each intersection point. The intersection point with smallest distance to the remaining circle is chosen as final point for the resulting triangle. Just as in the first case, our region of interest is formed by the circumcircle of the resulting triangle. If more than three measurements are performed, this approach is also valid. Then we consider four triples of circles (1, 2, 3), (1, 2, 4), (1, 3, 4), and (2, 3, 4) separately. The triple with the smallest measurement error determines then the final region of interest.

VI. Concluding Remarks

Indoor localization is a very important challenge for autonomous robotics. Since GPS is not available indoors, other technologies have to be used. Bluetooth provides a promising approach to the indoor localization problem because it provides device services and additionally enables positioning, localization, and even self-localization of Bluetooth devices. Unfortunately, the signal strength indication is not easily mapped to a corresponding distance for localization. Therefore, localization methods have to be explored in order to acquire accurate and robust position estimation.

VII. Acknowledgement

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 643892.

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