1 Introduction

Localization is a very important technology to promote the quality of human life. The awareness of one's own location is essential when we are in a totally new environment. Outdoor localization can be realized with the Global Positioning System (GPS). However, GPS does not work well indoors due to the blockage of buildings. Nowadays more and more automated robots are used in industrial indoor environments and the accurate position estimation for these robots is essential for the robots collaboration. The precondition for human-robot collaboration is that the distance between human and robot can be accurate detected. Thus the position of the workers also need to be accurate tracked. In the above mentioned and lots of other indoor applications, the indoor position estimation plays a crucial role. Many technologies have been developed for indoor localization, such as ultra wideband (UWB), infrared (IR) and light detection and ranging (Lidar). The indoor localization system can be used in many areas, for instance, in healthcare to track patients' position so that their safety can be improved, in the retail industry to improve the supply chain, or in logistics to optimize the overall workflow, etc. For different applications, a suitable localization system can be determined according to cost of the system, the required accuracy, the system capacity, and so forth.

In a conventional production line, industry robots need to be isolated by safeguards (e.g. safety fence, light curtain.) to guarantee the safety of the workers. The main disadvantage of using the fixed installation of safeguards is the reduction of productivity and flexibility. The fast free movement of industrial robots can dramatically improve flexibility, and various tasks can be finished by different combinations of these robots, so that the production line can have a faster response to rapid market-demanded change. Thus, the CR department in Bosch (China) Investment Ltd. has built a project called "Real-time Safety Virtual Positioning" (RSVP) to enable agile production systems by removing the fixed safeguard installation with the help of an safety indoor localization system. Instead of isolating the robots with safeguards, the safety of the workers is guaranteed based on the continuously measured distance between the robots and the workers. Two different circle zones are defined: the warning zone and the danger zone. The radius of the danger zone is the short safety distance (SSD), while the radius of the warning zone is the long safety distance (LSD), as shown in Fig. 1.1. If a human is in the warning zone, the robot moves more slowly. Once the human steps into the danger zone, the robot stops immediately. With the help of this function, the safeguards can be replaced with the indoor localization based safety system [WZD+19].

One of the most important parts of this system is the accurate position estimation of the robots and humans. Other factors, such as update rate, system capacity, system complexity and coverage., also need to be considered. Thus, a survey for the most widely used indoor localization system is conducted. This section presents an overview and comparison of these systems. It also shortly introduces the RSVP project and explains why UWB is the most suitable localization system for this project. Finally, it presents the main contributions and the structure of this thesis.

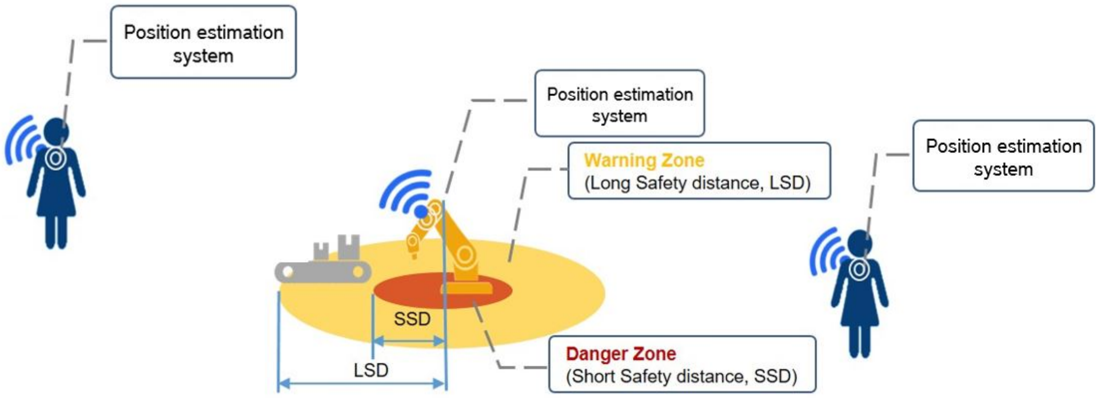

Figure 1.1: Concept of the safety function system in RSVP

1.1 Indoor Localization Systems

GPS is used to realize outdoor localizations. However it does not work well indoors, since the signals can be blocked by buildings. Thus, different systems have been developed for accurate indoor position estimation, such as UWB, IR and Lidar. Based on the utilized technologies and the position estimation algorithms, the most widely used localization systems can be roughly divided into four different groups: wireless based systems, IMU based infrastructure-free indoor localization, SLAM and visible light or acoustic based systems. This is shown in Fig. 1.2 [ZWL19].

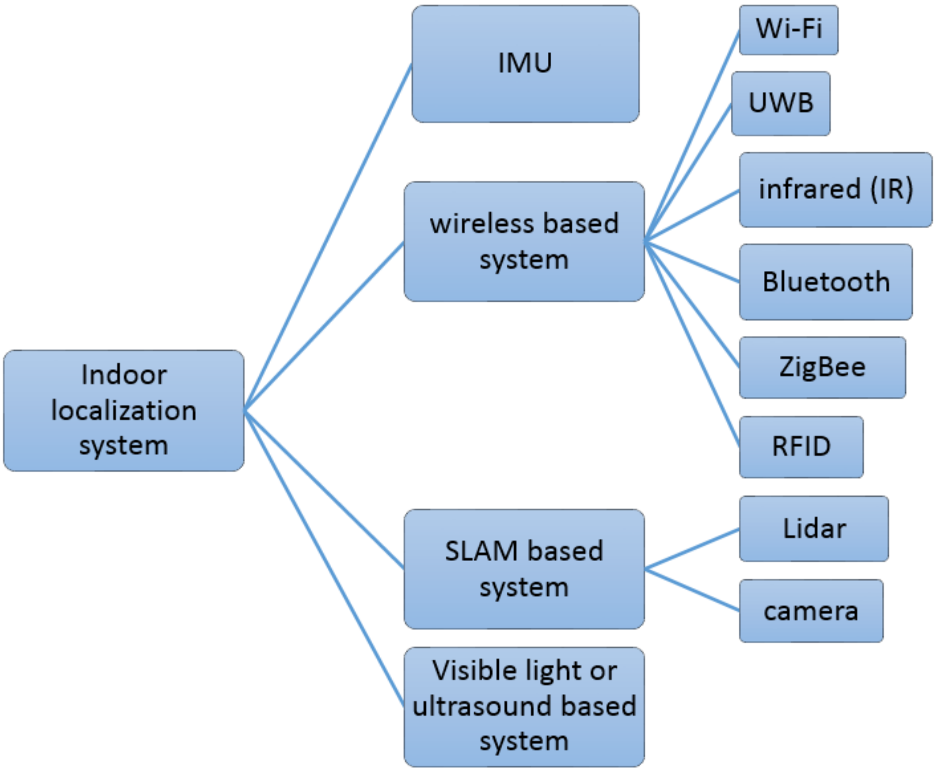

Figure 1.2: Overview of the most widely used indoor localization systems [ZWL19]

1.1.1 Wireless Based Indoor localization

In wireless systems, the information or power is transferred without wires or cables. The basic architecture for a wireless based position estimation system contains three parts: base stations (BSs), mobile stations (MSs) and the software to calculate the position of the MSs based on the measurements. The MSs are used to send the wireless signal to the BSs. Given the received signals in the BSs, different measurements can be obtained, such as the range between a BS and MS, the range difference, the received signal strength or the angle of arrival. Depending on the type of the measurements, different algorithms can be used for position estimation in wireless systems, such as the time of arrival (TOA), time difference of arrival (TDOA), angle of arrival (AOA) and received signal strength (RSS) [LJXG18], [CLL18], [SMS12], [ZYC$^+$13], [GZT08a]. These algorithms are realized in the software so that the real-time position estimation of the MS can be achieved.

Wireless Systems for Indoor Localization

Wi-Fi, UWB, IR, Bluetooth, ZigBee and radio-frequency identification (RFID) are all wireless technologies.

UWB: UWB is one of the most widely used wireless indoor localization systems due to its low-power consumption, high accuracy, robust operation in harsh indoor environments and low complexity for indoor applications. BSs and MSs are the basic components in UWB systems. The MSs send short signal pulses over a broad spectrum, and the BSs receive the signals. Based on the arrival time, the range or range difference measurements can be calculated.

Wi-Fi: Wi-Fi follows the standards in IEEE 802.11. Since Wi-Fi infrastructures already exist, the low cost is one of the main advantages of the Wi-Fi based localization system.

Zigbee: Zigbee technology is based on the standards in IEEE 802.15.4. Three bands can be used in Zigbee: the 2.4 GHz ISM band, 915 MHz band, and 868MHz band. The transmission rate for Zigbee is between 20 kbps and 250 kbps [OCC^{+}17].

Bluetooth: As a short-range wireless technology, Bluetooth is widely used in mobile phones and computers, etc. to transmit information in short ranges. The main advantages of Bluetooth are its lower power consumption, lower costs, and smaller size [HAG17].

RFID: The readers, tags, and servers are the basic components of RFID. The tags are identified and tacked based on the electromagnetic fields in RFID. There are three types of tags: passive , active and semi-passive tags. There are no batteries in the passive tag. The energy used in this tag is obtained from a nearby RFID reader. Active tags have an internal power supply (e.g. battery). Thus, information can be actively sent from the active tag to the reader. Compared to passive tags, active tags are larger and more expensive, but they have more functionalities [Bd08]. Semi-passive tags have internal power supply to power the circuitry, but the way of communication between tags and readers is the same as passive tags.

Infrared: infrared wavelengths are longer than those of visible light. Thus, infrared is invisible to humans. However, humans can feel it as heat. Infrared can be used for localization.

Position Estimation Algorithms for Wireless Systems

The output measurements of these wireless systems can be range, range difference, angle of arrival or received signal strength. Depending on the type of measurement, four different localization algorithms can be used for position estimation of the MS:

TOA, TDOA, AOA and RSS.

1) TOA: The range, which is defined as the distance between the MS and the BS, is used in TOA for position estimation. The position of the tag must lie on the circle that is centered at the BS. In the ideal case, the MS position is the unique intersection point of at least three different circles, with the ranges as the radii. In Fig. 1.3(a), the black intersection point is the position of the MS. The centers of the circles are the positions of the BSs. However, due to the existence of system noise error, the intersection of these circles is not a point but an area. The real MS position can be anywhere in the area. The larger the noise error, the greater is the intersection area and the more inaccurate the obtained position estimation for the MS might be. In Fig. 1.3(b), the real position of the MS can be anywhere in the green intersection area. Many algorithms have been developed to reduce the noise error, such as the least squares method (LS), the Taylor series method (TS), the approximate maximum likelihood method (AML) [GZT08a], and the Kalman filter (KF) [YDH16].

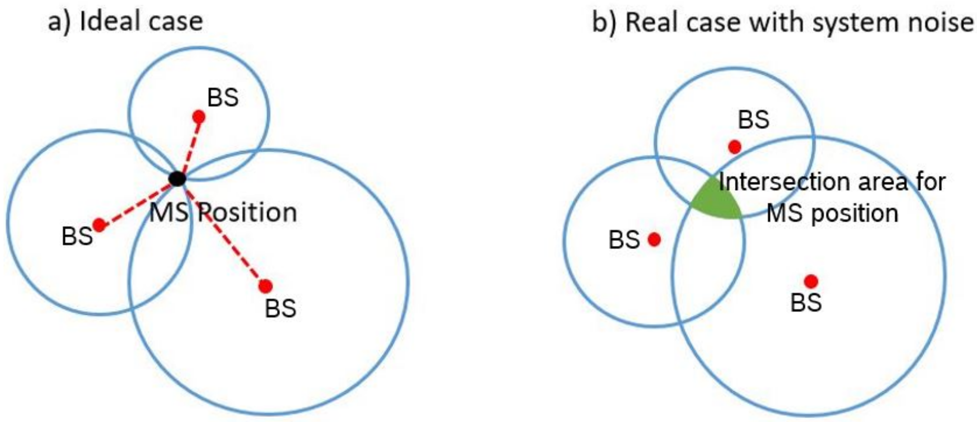

Figure 1.3: (a) TOA localization in an ideal case; (b) TOA localization in a real case with system noise error

2) TDOA: The difference between two ranges can also be used for position estimation. As shown in Fig. 1.4(a), if the difference between the distance from MS to BS1 and the distance from MS to BS2 is constant, then the trajectory of the MS is a hyperbolas. Thus, the intersection of the hyperbola, which are generated based on the range differences with foci at the BSs, is the position of the MS, as shown in Fig. 1.4(a).

3) AOA: Localization can also be achieved with the measured angles. As shown in Fig. 1.4(b), the angles α_1 and α_2 are the measurements. The position of the MS is the black intersection point of two straight lines.

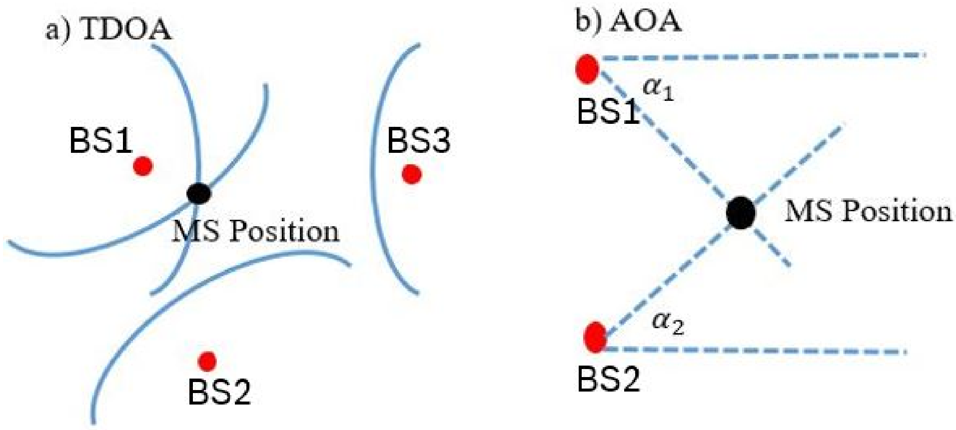

Figure 1.4: (a) TDOA localization; (b) AOA localization

4) RSS: Two different methods can be used to realize the localization based on RSS. The first one is based on the pathloss model, and the second on the fingerprint algorithm.

4.a) Pathloss model based algorithm: In this method, the pathloss model is built and used to determine the range. For example, the pathloss model for UWB can be written as follows [GJD+07]:

$$P_r = P_0 - 10nlog_{10}\frac{d}{d_0} + S \tag{1.1}$$

where d_0 is the reference distance, and P_0 is the received signal strength with distance d_0. The pathloss exponent is represented by n and S is a zero-mean log-normal random variable. Based on this model, the UWB ranges can be calculated and the position estimation can then be realized with the obtained ranges.

4.b) Fingerprint based algorithm: This method comprises two different phases, an off-line and an on-line phase. In the off-line phase, the RSSs at different reference locations are collected to build the database. During the on-line phase, the new measured RSS is compared with the collected RSSs in the database. Based on the comparison, the position estimation can be realized [YXW17].

1.1.2 IMU Based Infrastructure-free Indoor Localization

A 9-axis IMU system contains a 3-axis gyroscope, 3-axis accelerometer and 3-axis magnetometer. Pedestrian position estimation can be achieved based on IMU. Theoretically, by integrating the measured accelerations twice, the moving distance can be calculated. The orientation information can be obtained based on the measurements from the magnetometer and gyroscope. However, the calculated distance drifts away in a short period of time due to the biases in the acceleration measurements. Because of the drift errors, the IMU localization accuracy is not so promising. To improve this performance, Pedestrian Dead-Reckoning (PDR) is developed and used as an infrastructure-free methodology for pedestrian localization based on IMU.

The IMU is mounted on the foot of a human. The basic steps of the PDR algorithm are step counting; orientation information computation; step length calculation; finally, position estimation. The step counting can be realized by detecting the stance and swing phase of the foot based on the variance of the accelerations or the angular velocities, etc. [ZLWW17].

The calculation of the orientation (e.g. Euler angles or quaternion) is achieved based on the measurements from magnetometers and gyroscopes. By integrating the acceleration, the step length can be obtained. During the stance phase of each step, the foot velocities should be zero after the integration of the acceleration. However, since biases exist in the accelerations, the foot velocities are not zero. Theoretically, the calculated velocities in the stance phase are equal to the integration of the biases. Thus, the biases can be calculated using these velocities. Based on this principle, the drift error can be reduced. The position estimation can be achieved with the calculated step numbers, step lengths and orientation information.

1.1.3 Simultaneous Localization and Mapping (SLAM)

In general, simultaneous localization and mapping (SLAM) is a technique for building a map of an unknown environment and estimating positions. This technology has been used in many areas, such as in robots, autonomous cars, unmanned aerial vehicles, and augmented reality (AR). Lidar and cameras are the most widely used sensors for SLAM.

Compared to camera based SLAM, localization based on light detection and ranging (Lidar) is more accurate. The distance between the target and the Lidar can be measured with the help of a laser.

On the other hand, using a camera is cheaper and can provide more visual information compared to Lidar. There are three different kinds of cameras for SLAM application: monocular, stereo and RGB-D cameras. A monocular camera contains only a single camera, while a stereo camera has two cameras. Besides an RGB image, the distance between the camera and the object is also provided by the RGB-D camera. Camera based SLAM can be realized with four steps: visual odometry, back end, loop closing and mapping.

1) Visual odometry (VO): The translation and rotation between adjacent frames are determined and used as initialization values for the back end. There are three different methods to calculate the camera motion: the feature based method [MMT15], optical

flow [WCD$^+$16] and direct method [FPS14].

2) Back end: The camera motions are optimized with frames taken at different times based on the extended Kalman filter, bundle adjustment, pose graph, and so forth [SP12].

3) Loop closing: The main task of loop closing is to identify whether the camera has returned to the previous area.

4) Mapping: Based on the estimated camera motions, the map can be built.

1.1.4 Visible Light or Ultrasound Based Indoor Localization

Position estimation can also be realized based on visible light. The most widely used element in the visible light system is the light-emitting diode (LED). The TOA, TDOA, RSS and AOA position estimation algorithms can also be used in an LED localization system. A method is proposed in [MSM08] to determine the position and the direction of the receiver based on visible LED lights and image sensors.

Sound waves with frequencies higher than 20 kHz (upper limit frequency of human hearing) are defined as ultrasound. Like wireless systems, the TOA and TDOA algorithms are also applied in ultrasound systems for localization purposes.

1.2 Comparison of Localization Systems

Each of the presented localization systems has its own advantages and disadvantages. Several factors can be considered to select the most suitable system for different indoor applications, such as cost, position estimation accuracy, update rate, system capacity, coverage area, system complexity and power consumption. The position estimation frequency of the system per second is defined as the update rate. The costs for indoor localization systems can differ widely. Normally, the more accurate the system is, the more expensive it is. The system capacity determines how many devices can be used at the same time. For the RSVP project application, the following factors are the most important in selecting the localization system.

1) Accuracy: The position estimation accuracy is the most important factor to guarantee human safety. The system should be able to continuously provide the precise location of humans and robots so that the distances between them can be monitored with a relatively high frequency. Furthermore, the more accurate the system is, the smaller the SSD and LSD zones are and the more space can be saved for further applications.

2) Update rate: When humans move fast, if the update rate is too low, the human could already be in the danger zone, and the real-time distance may not be updated yet or the robot may move too fast and not be stopped in time. This could be very dangerous for the workers.

3) System capacity: In the production line, the number of workers and robots could be more than 100. Thus, the system must be able to provide enough devices, that can be used for localization at the same time.

4) System complexity: To maintain the flexibility of the system, its complexity should be low. The easy installation and easy adding or removing localization devices after the installation are required.

5) Coverage: The system should be able to cover the whole working area. In the RSVP project, the coverage should be at least 25 m.

6) Cost: The cost of the system needs to be kept in an acceptable range.

The comparison of the localization accuracy, coverage area, complexity and cost of different systems can be found in Table 1.1. As shown in the table, compared to Wi-Fi, Bluetooth, ZigBee and RFID, UWB has better accuracy and its coverage meets the requirements. The SLAM based solutions are even more accurate than UWB, but the cost of hundreds of Lidar SLAM devices is much higher. Due to the confidential environments in the production line, cameras are not a good option. Furthermore, once the direct signal propagation path is blocked, many localization systems become inaccurate. However, UWB can still provide accurate measurements if the blockage only comes from, for instance, thin tables, counters or glass. The update rate of UWB can exceed 90 Hz, which is more than enough for the RSVP project. With the developed UWB system in the project, 100 localization MSs with an update rate of 20 Hz can be used at the same time. The cost of the system is acceptable. Thus, the UWB localization system is the best option for the RSVP project application.

1.3 General Information on UWB

Despite the advantages of UWB, some challenging problems remain for UWB based indoor localization, such as the inaccurate position estimation caused by NLOS errors. First, this section presents a short introduction to the UWB system. Due to the fine time resolution of the UWB signals, the time based TDOA and TOA stands in the focus in this thesis, since they offer very good accuracy. The basic principle of time based UWB localization can be explained as follows. The MS sends the UWB pulse to the BSs. The BSs receive the signals from direct paths, reflected paths, etc. and then provide the channel impulse response(CIR). Given the CIR, the arrival time can be obtained. With the help of the sending time from the MS, the signal propagation

Table 1.1: Comparison of different localization systems [Liu14], [XZYN16], [Mau12], [MPS14], [LDBL07] , [ZGL17]

	Accuracy	**Coverage (m)**	**Complexity**	**Cost**
Wi-Fi	m	20-50	low	low
UWB	cm-m	1-50	low	low/medium
Infrared (IR)	cm-m	1-5	low	medium
Bluetooth	m	10	low	low
ZigBee	m	30-60	low	low/medium
RFID	dm-m	1-50	low	low
IMU	1%	10-100	low	low
Vison	0.1mm-dm	1-10	high	high
Ultrasound	cm	2-10	low	low

time from the MS to the BSs can be calculated. Based on these time measurements, the range (for TOA) or the range difference (for TDOA) can be obtained and used for position estimation. However, these data suffers from noise errors and NLOS errors. Inaccurate localization is mainly caused by NLOS errors. Different methods have been developed for NLOS mitigation, such as the Kalman filter (KF) and particle filter (PF), which are combined with CIR based NLOS identification, IMU sensor based NLOS mitigation and so forth. In summary, UWB based localization can be divided into the following parts, as show in Figure 1.5:

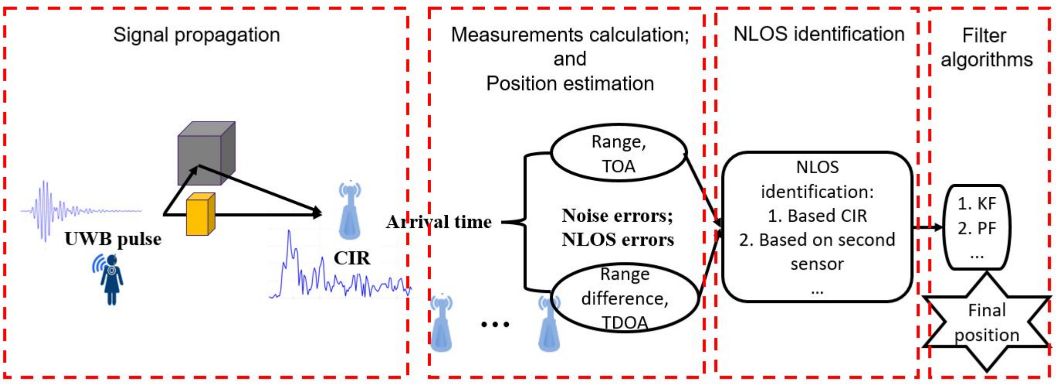

Figure 1.5: UWB based localization process

1. Signal propagation: The MS sends the signals and the BSs obtain the signals. The final results in this phase are the CIRs provided by the BSs.

2. Measurements calculation: Based on the CIRs, the signal arrival time can be ob-

tained. With the help of the arrival time and signal sending time, the range (for TOA) or the range difference (for TDOA) can be calculated.

3. Position estimation: Based on TOA or TDOA, the final position can be computed.

Additional methods to improve the localization accuracy are the following:

4. NLOS identification: NLOS identification can be realized using CIRs or a second sensor source, such as IMU, etc.

5. Filter algorithms: KF and PF.

UWB signal propagation and channel estimation have been discussed in many papers [LDM02], [CLLW16], [CSW02], [WRSB97], [WS02]. However, these propagation models are mostly for communications. Few papers include a detailed discussion about the relationships between CIRs and accurate/inaccurate measurements. Measurement calculation with one-way range or two-way range is described in [Utt15], [Decb]. Based on the different types of measurements (range, range difference, etc.), different methods have been developed for position estimation, such as TOA, TDOA, AOA and RSS, as discussed in Section 1.1.1. The main factor that causes inaccurate localization is the NLOS error. NLOS identification is the most powerful approach to reduce this error. The overview of NLOS identification and mitigation is provided in chapter 4. Although UWB localization systems have been discussed in many papers, there are still some unanswered or not fully answered questions. From the influence of the signal propagation path for the CIR to the final error mitigation algorithms, this thesis aims to provide a detailed overview of UWB based localization. As shown in Figure 1.6, the answers to the following questions in different phases for the UWB based localization process are given in this thesis:

During signal propagation:

1. How do the channel paths affect the CIRs?

2. Do all blockages cause inaccurate measurement?

During measurement calculation:

1. What does the LOS/NLOS noise distribution look like?

2. What is the relationship between the CIRs and NLOS/LOS measurements?

During position estimation:

1. What is the difference between TDOA and TOA?

2. Under which conditions is TDOA more suitable than TOA?

During NLOS identification:

1. What are the different NLOS identification methods?

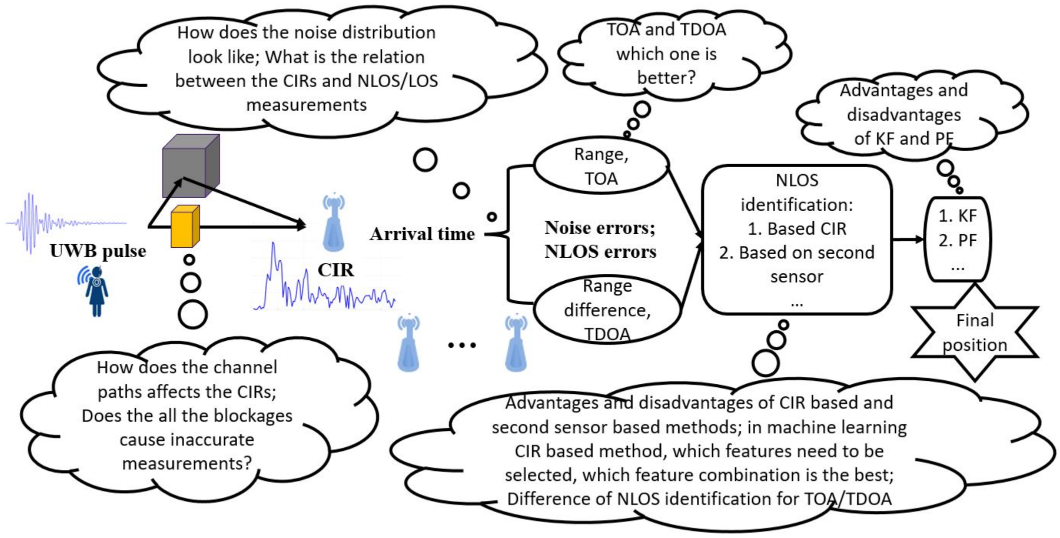

Figure 1.6: Overview for the UWB based localization process

2. What are the advantages and disadvantages of CIR based and second sensor based methods?

3. In machine learning CIR based methods, which features need to be selected, and which feature combination is the best?

4. What is the difference in the NLOS identification for TOA and TDOA?

During filter algorithms:

1. What are the advantages and disadvantages of KF and PF for UWB based indoor localization applications?

Based on the answers to these questions, this thesis shows that NLOS identification is the most effective method to improve UWB localization accuracy. Thus, NLOS identification stays in the focus in this thesis.

1.4 NLOS Identification for UWB

As described above, UWB based localization is not new. The range based TOA, range difference based TODA, angle based AOA and received signal strength based RSS position estimation algorithms for UWB have been discussed in many papers. Different filters, such as the Kalman- and particle filter, can be used to reduce the system random error. Under line of sight condition, where no blockage exists between the MS and BS, accurate UWB based localization can be achieved. The challenge arises if the signal propagation path is blocked, which is defined as NLOS. A non-negligible bias is added to the measurement under NLOS conditions, which leads to inaccurate position estimation if the NLOS measurement is used for localization calculation. The accurate NLOS identification is the key factor to guarantee UWB based accurate position estimation. Most of the current approaches can be summarized as follows.

Without a detailed investigation of the LOS/NLOS error, many approaches assume that the errors model can be treated as a Gaussian distribution, and they use the Kalman filter to identify and mitigate the NLOS errors. However, NLOS errors differ with different blockage materials. These errors can be any random values. Thus, a Gaussian distribution is not a good description of the NLOS error model.

Some papers assume that the variance of the NLOS measurements is theoretically larger than that of the LOS measurements. By using a suitable threshold to compare with the variances, NLOS detection can be achieved. However, if the blockage is the same and the distance between the BS and MS does not change dramatically, the variance of the NLOS errors can be smaller than the variance of the LOS errors. Thus, NLOS detection accuracy is not very promising. Besides, the proper threshold is highly difficult to be determined, and the latency can not be avoided due to the collection of the ranges for the variance calculation.

Other methods utilize additional information for the NLOS detection, such as RSS or a map of the floor. However, RSS is highly dependent on the indoor environments. With humans coming in or going out, the RSS could change dramatically. Besides, the threshold used to compare with the RSS is highly difficult to be determined. With an improper threshold, the accuracy can be very poor. The main disadvantage of the map based method is that the maps are not always available. Except for the fixed furniture, there are many of moving objects or humans. The NLOS detection accuracy based on these methods is not sufficient.

One of the most effective methods of NLOS identification is based on CIR. The current CIR based NLOS detection works only for TOA. Furthermore, the reasons for selecting the useful features have not been explained, and the optimization of the feature combination and the parameters in machine learning algorithms has not been discussed.

In summary, the current NLOS identification and mitigation methods have the following drawbacks:

1) The error model of the UWB measurements has not been discussed in detail. Thus, improper models are assumed and used for identification.

2) The relationship between the CIRs and the accurate/inaccurate range measurements has not been fully described. Not all blockages lead to inaccurate measurements. A detailed description of the conditions that cause the NLOS is still missing.

3) An overview and comparison of the current NLOS identification methods are miss-

ing.

4) Although TOA and TDOA are discussed in many papers, they are barely compared based on the localization environment perspective. The range measurements are used for localization in the TOA method. Under the condition that the NLOS condition can be properly identified, this method works very well in the environments where NLOS does not occur very frequently, such as offices. However, in harsh industrial environments where NLOS happens frequently, even with the help of the NLOS identification approach, this method might not provide accurate position estimation since it can happen that not enough accurate ranges can be obtained. In these environments, TDOA which used the range difference for position estimation can be more accurate than TOA, since the biases of two different NLOS ranges can be compensated and an accurate range difference can be obtained even under NLOS condition. If the accurate range difference can be selected, accurate localization can be guaranteed. However, most current approaches only discuss NLOS detection for the selection of the accurate ranges, and do not work well for the accurate range difference selection in TDOA.

5) The fusion of IMU and UWB is one of the most widely used methods to improve localization accuracy. Most current fusion approaches are based on the extended Kalman filter with the assumption that the errors are Gaussian distributed. The NLOS outliers are detected based on predicted Gaussian distribution error models. However, in reality, NLOS errors are not Gaussian distributed.

To further improve the NLOS identification and UWB based localization accuracy, in this thesis, the UWB measurement errors are investigated. LOS and NLOS errors are discussed separately. LOS errors are evaluated in office and industrial environments with different distances. For NLOS errors, different blockage materials and blockage conditions are considered. The LOS and NLOS error models can only be built based on the experimental investigation since the theoretical modeling can not be achieved in different test environments. Systematic experimental investigation on NLOS effects have been done in office and industrial environments. The relationship between CIRs and accurate/inaccurate range measurements is described in detail. Furthermore, the thesis presents an overview of the current NLOS identification methods. Four different NLOS identification and mitigation approaches are developed in this project. The first one works for the TOA approach in an office environment with a stand-alone UWB system, while the second one works in harsh industrial environments. The third and fourth one are UWB/IMU fusion approaches, and they work for TOA/TDOA methods.

1.5 Outline and Contributions

To further improve NLOS identification and localization accuracy, the following investigations are conducted.

First, the UWB system is systematically analyzed, and the possibility to build general error models based on collected UWB measurements is evaluated. It is found that although the noise distribution under LOS can be modeled as a Gaussian distribution, a general error distribution model under NLOS is difficult to build due to the unstable NLOS error. The error model is different depending on the environment. Specifically, for the Bosch Shanghai office, an approximate stable distribution model can be used to describe the error distribution based on our investigation. Although the localization performance can be improved with properly built error distribution models, NLOS measurements still have an influence on the position estimation accuracy in the field test.

Next, the thesis describes UWB signal propagation in detail. The relationship between the CIRs and the accurate/inaccurate range measurements is theoretically discussed in three different situations: ideal LOS path, small-scale fading: multipath, and NLOS path. The theoretical relationship is validated with real measured CIRs in Bosch Shanghai office environment. It is found that not all blockages lead to inaccurate measurements. The thesis explains when and why the blockages cause inaccurate measurements.

Next, the thesis presents an overview of NLOS identification for the TOA method. It shows that CIR based- and second sensor based NLOS detection are two of the best approaches from the perspective of the NLOS detection accuracy and engineering feasibility. For the current CIR based NLOS detection, a summary of the features and the optimization of the feature combination as well as the parameters in machine learning are missing. In this thesis, an overview of the possible useful features are given. Based on the difference in CIRs of the accurate and inaccurate range measurements, five different feature groups are created according to distance, CIR shape, time, multipath richness and power related features. In each group, several features can be extracted. With these features, NLOS identification is realized based on the SVM method. The optimal feature combination is theoretically determined and validated with real measurements. The parameters in SVM are optimized. The localization accuracy shows highly promising improvements based on the particle filter with the NLOS identification compared to the traditional methods in the Bosch Shanghai office environment.

The thesis then presents the difference between the TOA and TDOA. It shows that in harsh industrial environments, where NLOS conditions frequently occur, the localization accuracy improvement based on particle filter with the NLOS identification TOA are limited. A novel approach is proposed which combines TOA and TDOA method with accurate range and range difference selection. The position estimation accuracy is improved with this approach compared to the other approaches during a field test in the Bosch Changsha plant.

Different to the current UWB/IMU fusion approaches, which detect inaccurate UWB measurements based on the assumption that the errors are Gaussian distributed, in this paper, the triangle inequality theorem is used to select the accurate ranges for TOA or the accurate range differences for TDOA based on the IMU measurements. The Gaussian distributed error models are not needed for the proposed approaches. The position estimation accuracy is improved with the proposed approach compared to the traditional methods in the Bosch Shanghai office.

1.5.1 Contributions

In summary, the main contributions of this thesis are follows:

1) This thesis investigates LOS/NLOS errors in different environments under different situations. Based on the investigation, an approximate stable distribution model is built to describe the error distribution in the Bosch Shanghai office.

2) The relationship between the CIRs and the accurate/inaccurate range measurements is theoretically discussed and validated with the real measured CIRs in the Bosch Shanghai office environment. The thesis explains when and why the blockages cause inaccurate measurements.

3) The extracted features from CIR for NLOS detection are divided into five different groups. The optimal feature combination is theoretically determined and validated with real measurements. Furthermore, the parameters in SVM are optimized.

4) The difference between TOA and TDOA is discussed from the localization environment perspective. Based on this discussion, a novel approach is proposed, which combines TOA and TDOA methods with accurate range and range difference selection.

5) The thesis proposes two UWB/IMU fusion approaches that utilize the triangle inequality theorem to select accurate ranges for TOA or accurate range differences for TDOA based on IMU measurements. Gaussian distributed error models are not needed for the proposed approaches.

1.5.2 Outline

This thesis is organized as follows.

Chapter 1 briefly introduces the "Real-time Safety Virtual Positioning" (RSVP) project and provides an overview of the existing indoor localization systems. After the comparison of these position estimation systems, the UWB system is determined to be suitable for the project. A short overview of UWB is provided. Finally, the outline and main contributions of this thesis are described. This chapter is partly based on the following papers:

W. Wang, Z. Zeng, W. Ding, H. Yu and H. Rose, "Concept and Validation of a Large-scale Human-machine Safety System Based on Real-time UWB Indoor Localization*," 2019 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), Macau, China, 2019

Z. Zeng, L. Wang and S. Liu, "An introduction for the indoor localization systems and the position estimation algorithms," 2019 Third World Conference on Smart Trends in Systems Security and Sustainablity (WorldS4), London, United Kingdom, 2019

Chapter 2 describes the UWB system in detail. It provides an overview of the factors that influence UWB localization accuracy. These factors are the antenna, installation of the BSs, time synchronization, localization algorithms, NLOS/LOS identification, and filter algorithms. The signal propagation path is introduced. The measurement error is investigated. The relationship between CIRs and accurate/inaccurate measurements is theoretically explained for three different cases: ideal LOS path; small-scale fading: multipath; NLOS path. Furthermore, the chapter investigates the UWB range measurements error under clear LOS/multipath LOS, ignorable NLOS blockage and non-ignorable NLOS blockage.

Chapter 3 focuses on the localization filter problem. The Kalman filter principle is presented. It shows that Kalman filter can provide estimated state vectors with minimized variances for linear problems with Gaussian noise. Extended Kalman filter at the same time can be used for non-linear problems with Gaussian noise. However, based on the experiment results, it might suffer from a divergent problem with the frequently changing measurement noise. IEKF is more stable compared to EKF. The particle filter can be used to solve non-linear problems with non-Gaussian noise. PF is more stable compared to IEKF based on the experiment results. However, PF has the highest computation load.

Chapter 4 provides an overview of the NLOS identification methods: these methods are based on range variance estimation, combination of RSS, map, CIR, CIR state change and IMU. The chapter compares these methods' identification accuracy, engineering feasibility, and so forth. After the comparison, it can be determined that CIR based- and IMU based NLOS identification are two of the best approaches.

Chapter 5 focuses on the UWB localization in office environments. First, the localization with three BSs is discussed. The error distribution is found to be stable distribution. Since the system is non-linear and the error distribution is not Gaussian, the PF is used for position estimation. Although it can be observed that the localization accuracy is improved with a properly defined error distribution, the NLOS error is still severe. A better solution to further improve the accuracy is to add redundant BSs and use only the selected accurate ranges based on NLOS identification for further calculation. The SVM algorithm is used for NLOS detection. Five different feature groups are divided based on the distance, CIR shape, time, multipath richness and power related features. The reasons why these features can be used for classification are explained.

The feature combination, the used CIR length and the parameters in SVM are optimized to improve the identification accuracy. It can be observed in the field test that, the localization accuracy with NLOS identification is dramatically improved.

Chapter 6 presents UWB localization in harsh industrial environments. NLOS conditions occur more frequently in harsh industrial environment than in office environments. In the Bosch Changsha plant, it often happens that less than two ranges are measured under LOS. The position estimation with the NLOS identification based TOA approach does not have very good accuracy. Hence, an accurate ranges and range differences identification based TOA/TDOA combination approach is proposed to improve position estimation accuracy. Two SVM models are trained. The first one is used to select the accurate ranges, which is the same as the one presented in Chapter 5. If at least three ranges are detected as accurate, then the localization can be realized with these ranges. Otherwise, the range differences need to be calculated with the inaccurate ranges. The second SVM model is used to select the accurate range differences. These accurate ranges and range differences are used for position estimation. The particle filter is used to realize the localization together with the accurate ranges and range differences identification based TOA/TDOA combination approach. The position estimation with the proposed TOA/TDOA combination approach shows better accuracy than the NLOS identification based TOA approach and the standard TOA approach in the Bosch Changsha plant.

Chapter 7 focuses on UWB/IMU fusion localization. The IMU measurements are used to identify and mitigate UWB NLOS errors. The fusion system can be used for both TOA and TDOA based on UWB localization. With the help of IMU measurements, the accurate ranges for TOA or the accurate range differences for TDOA can be determined based on the triangle inequality theorem. The localization performance with the UWB/IMU fusion system is evaluated in the Bosch Shanghai office. The localization accuracy is improved with the proposed methods compared to the methods without the fusion with IMU. This chapter is based on the following papers:

Z. Zeng, S. Liu, and L. Wang. Uwb/imu integration approach with nlos identification and mitigation. In 2018 52nd Annual Conference on Information Sciences and Systems (CISS), pages 1-6, March 2018.

Z. Zeng, S. Liu, and L.Wang. A novel nlos mitigation approach for tdoa based on imu measurements. In 2018 IEEE Wireless Communications and Networking Conference (WCNC), pages 1-6, April 2018.

Chapter 8 summarizes this thesis and provides the conclusions.

1.6 Publications

The following papers are published during the PhD studies:

Z. Zeng, S. Liu, W. Wang and L. Wang, "Infrastructure-free indoor pedestrian tracking based on foot mounted UWB/IMU sensor fusion," 2017 11th International Conference on Signal Processing and Communication Systems (ICSPCS), Surfers Paradise, QLD, 2017, pp. 1-7. doi: 10.1109/ICSPCS.2017.8270492

Z. Zeng, S. Liu and L. Wang, "NLOS Identification for UWB Based on Channel Impulse Response," 2018 12th International Conference on Signal Processing and Communication Systems (ICSPCS), Cairns, Australia, 2018, pp. 1-6. doi: 10.1109/ICSPCS.2018.8631718

Z. Zeng, S. Liu and L. Wang, "UWB/IMU integration approach with NLOS identification and mitigation," 2018 52nd Annual Conference on Information Sciences and Systems (CISS), Princeton, NJ, 2018, pp. 1-6. doi: 10.1109/CISS.2018.8362197

Z. Zeng, S. Liu and L. Wang, "NLOS Detection and Mitigation for UWB/IMU Fusion System Based on EKF and CIR," 2018 IEEE 18th International Conference on Communication Technology (ICCT), Chongqing, 2018, pp. 376-381.

Z. Zeng, S. Liu and L. Wang, "A novel NLOS mitigation approach for TDOA based on IMU measurements," 2018 IEEE Wireless Communications and Networking Conference (WCNC), Barcelona, 2018, pp. 1-6. doi: 10.1109/WCNC.2018.8377041

Z. Zeng, S. Liu and L. Wang, "UWB NLOS identification with feature combination selection based on genetic algorithm," 2019 IEEE International Conference on Consumer Electronics (ICCE), Las Vegas, NV, USA, 2019, pp. 1-5.

Z. Zeng, R. Bai, L. Wang and S. Liu, "NLOS identification and mitigation based on CIR with particle filter," 2019 IEEE Wireless Communications and Networking Conference (WCNC), Marrakesh, Morocco, 2019, pp. 1-6, doi: 10. 1109 / WCNC. 2019. 8886002.

W. Wang, Z. Zeng, W. Ding, H. Yu and H. Rose, "Concept and Validation of a Large-scale Human-machine Safety System Based on Real-time UWB Indoor Localization*," 2019 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), Macau, China, 2019, pp. 201-207, doi: 10.1109/IROS40897.2019.8968572.

Z. Zeng, L. Wang and S. Liu, "An introduction for the indoor localization systems and the position estimation algorithms," 2019 Third World Conference on Smart Trends in Systems Security and Sustainablity (WorldS4), London, United Kingdom, 2019, pp. 64-69, doi: 10.1109/WorldS4.2019.8904011.

Z. Zeng, W. Yang, W. Wang, L. Wang and S. Liu, "Detection of the LOS/NLOS state change based on the CIR features," 2019 Third World Conference on Smart Trends in Systems Security and Sustainablity (WorldS4), London, United Kingdom, 2019, pp. 110-114, doi: 10.1109/WorldS4.2019.8904000.