Exploration and Analysis of Sensor Technologies for Efficient Indoor Location based Services

Suguna P. Subramanian

Exploration and Analysis of Sensor Technologies for Efficient Indoor Location based Services

Dissertation
der Fakultät für Informations- und Kognitionswissenschaften
der Eberhard-Karls-Universität Tübingen
zur Erlangung des Grades eines
Doktors der Naturwissenschaften
(Dr. rer. nat.)

vorgelegt von
Dipl.-Inform. Suguna P. Subramanian
aus Gobichettipalayam, India

Tübingen
2010

Tag der muendlichen Qualifikation:	14. 07. 10
Dekan:	Prof. Dr.-Ing. Oliver Kohlbacher
1. Berichterstatter:	Prof. Dr. Wolfgang Rosenstiel
2. Berichterstatter:	Prof. Dr. Andreas Zell

To my daughter Adithi Velavan

Acknowledgement

My very first credit goes to my daughter, who was there during all my hardships and elation. She remains as one who rejuvenated me during hardship. I express my heartiest gratitude to my companion Dr. Velavan T.P for being a source of consistent encouragement and inspiration during the course of my dissertation. I thank my parents and my father in law for their consistent encouragement all through my academic career.

I am indebted and owe my absolute gratitude to Prof. Dr. Wolfgang Rosenstiel for providing me an opportunity to come to Germany to accomplish my PhD. I am really honoured to have him as my guide who is friendly yet stimulating me scholarly and for all the independency that he provided during my work period. I thank him for his constructive feedbacks that enabled me to gain knowledge on my research goals. I would like to thank him right from my heart for all the help that he has rendered during my tenure. Thanks for having faith in me and for all the motivation that he has rendered. I would like to thank Prof. Dr. Andreas Zell, my second supervisor, who provided an insightful view of my work.

I would express my deepest gratitude and feel extremely privileged to work with Dr. Stephen Schmitt. I extend my sincere thanks to him for his leadership qualities and able guidance all through my PhD. Fruitful discussions had made my career dynamic in all perspectives throughout the course of my dissertation. I would like to thank my colleague Juergen Sommer, for his skeptical questions and insightful comments and for reviewing my work. I am grateful to them for the patience they have shown during my discussions with them.

I thank Landesstiftung Baden-Wuerttemberg(in the scope of the BW-FIT project AmbiSense), Germany, for their financial support for my living and for all travel grants to attend conferences abroad. Many thanks to Margot Reimold for facilitating all administrative and organizing efforts.

I express my gratitude to my colleagues Michael Bensch and Werner Dreher for their technical assistance. I am most grateful to Dr. Prakash Mohan Peranandam, a down to earth guy who was always there to help me at any time, at any place, at any regard and at any cost.

I express my gratitude to Frank Peter Zeh for consistent help in conducting experiments. A special thanks to Dr. Axel Braun, Dr. Pradeep K. Nalla, Dr. Djones Lettnin and Dr. Julio Oliveria Filho whose input has provided me an ample opportunity to improve my dissertation. I extend my thanks to my co-PhDs Andreas Bernauer who used to converse with me often in German which motivated me to learn German language.

A special thanks to Traugott Dittmann (Muenster) for his friendship, and for the help rendered to me and to my beloved. I am proud to call him as my best friend I had.

A bunch of thanks to Sankar, Ravi and Jai for providing me a cosy Tamil environment during my stay here in Tuebingen and for all the help they rendered to me and my family during my dissertation period. I owe a lot to these guys.

I owe a lot of people, friends, colleagues, who helped me, supported me during my PhD. My sincere thanks to all if I have not mentioned them.

Abstract

In recent years, there is a mounting obligation for indoor location based services comparable to outdoor location based services. Indoor guidance systems provide ample utilities to a user explicitly at huge complex shopping malls, hospitals and at vast libraries for any directed assistance. Pedestrian navigation is one such promising indoor location based service. Localization remains a basis for all location based services. Although, few pedestrian based indoor localization systems are available in market, they lack either one of the attributes such as accuracy, reliability, scalability and/or expensive. GPS is not meant for indoors and even if so used at indoors, its relative weak signals still stay a hurdle for any indoor location based services.

In this dissertation, the aim is to build an efficient and precise indoor localization approach that can be implemented for most of the large indoor environments. The projected approach in this study incomparable to GPS that works outdoors, will remain eminent than other available indoor localization based approaches. All prerequisite for efficient localization such as accuracy, reliability, scalability, flexibility, availability, cost efficiency, minimum latency and robustness were evaluated for this reconstructed approach that is demonstrated herewith in my dissertation.

The dissertation is structured as various chapters. Each of the chapter in this dissertation portrays novel methods utilizing major sensor technologies such as Bluetooth, RFID and Inertial sensors for efficient indoor localization. The ultimate objective of the dissertation is well achieved. The reconstructed hybrid prototype system employing Bluetooth, RFID and Inertial sensors and remains universally adaptable for any of the location based services. The corresponding results were validated and substantiated for their accuracy and reliability and competence in comparison to available single and hybrid based sensor systems. In addition, a route planning algorithm developed for navigation in indoor environments completes the prototype.

Inhaltsverzeichnis

Abbildungsverzeichnis

Tabellenverzeichnis

1 Introduction

In the last two decades, communication by mobile phones had played a pivotal role in the rationalization of the society. Equivalently, in recent years there is an imperative exigency for location based services in mobile phones. A location-based service (LBS) in-term is an information based service provided to a mobile user by utilizing the localized position followed by interacting on an available network. A request to locate an Automated teller machine (ATM) or restaurants in the vicinity, locating an individual on a mapped environment are some examples for location based services. Localization is pedestal for all location based services.

Localization can be formulated as to determine an objects position in a two or three dimensional space constructs using a few reference points. This localized position can be demonstrated by means of global coordinates of earth namely latitude, longitude and altitude or by Cartesian coordinates (x, y, z with references as origin). Position localization can be achieved in two distinct perspectives: either as relative or as absolute. Relative position can be estimated by utilizing the orientation and pace in accordance with available data from previous position. Relative measurements remains accurate for shorter distance but the error accumulates on a long run. On the other side, the absolute position can be narrowed down by proximity estimation or by angular distance to the reference point. The absolute position remains reliable in comparison to relative position.

1.1 Background of Localization

In ancient days, the sailors made the most of their celestial knowledge to cross the ocean and the seas. This was well achieved by making angular measurements (sights) between celestial bodies in the sky to that of visible horizon. This means that celestial localization had been implemented those days for global positioning for both land and sea. At a specific time, any celestial body location can be determined by one specific geographic point or by specific coordinates on the earth namely the latitude and longitude. Increasing innovation in the field of electronic communications has led to a current trend of utilizing Global positioning system (GPS) or utilizing radio frequencies (sensors) for localization.

GPS is an U.S. based global navigation satellite system that was created and brought to fruition by the American Department of Defense (DOD) that made use of 24 satellites (21 satellites required for operational and 3 served as replacement). Currently, more than 30 active satellites orbit the earth at proximity of 20200 km. GPS based satellites transmit signals that in turn enables the exact location of a GPS receiver, if it is positioned on the surface of the earth, in the earth's atmosphere or in a low orbit.

GPS based satellites broadcast signals from space which provides a three-dimensional location (latitude, longitude, and altitude) of the user in addition to precise time. GPS satellites provides a reliable positioning, navigation, and timing services to users worldwide uninterrupted. GPS based satellites remain operational day and night at extreme weather conditions, either in proximity or on the planet earth. GPS had been employed in aviation, in navy as nautical navigation and for the orientation ashore. In addition, GPS is being employed to survey lands and with many other applications where there remains an obligation to obtain an exact position.

The only prerequisite in obtaining a GPS transmission signal is that one needs a unobstructed link to the satellites (or rather of the sky). GPS based localization remains impractical in indoor buildings. The alternative for localization in indoor environment is radio based localization systems. Radio based localization systems uses radio frequencies to determine a position on the space. The measurement is made back and forth by the radio beacons. The estimated position is calculated by several means such as measuring travel period (distance estimate), inferring direction (radio phases), interferometry, and velocity estimation (Doppler shift).

1.2 Applications of Localization

Emergency and the Navigation services: One vital application of location based services is tracking an individual in case of emergency such as natural calamities leading to risk to life, a fire in the warehouse and so on. In these emergency situations, the individual himself cannot rely on his senses to estimate his or her exact location. For instance, an individual will not be able to specify his or her own location when there is a vehicle break down on a long drive. On such occasions, network based localization will assist the individual in providing necessary services during such crisis in a rapid and efficient manner. Other alternative example can be, an individual needs to be familiar with the detailed directions to locate his desired destination to a hospital ward, a office in a multi-storey building, locating a book in a vast library. The chances of getting lost are much higher. For all above, location information remains pedestal for these location based services

Information Services: Location based information services mostly refer to the distribution of information based on user's location and behavior. Services such as personal guidance in museums, vital information on a place of interest such as in university buildings and emergency exits in an unknown indoor environment are ably provided to individuals.

Tracking and Management Services: Tracking services are used both in consumer and corporate markets. One popular example refers to tracking of a parcel or a postal package regarding the despatch destinations of these cargo, will be readily available at any time. Tracking and locating an individual inside a building or at an institute, tracking a product of choice in a shopping mall, get in track with books that were lend in a library, Tracking your vehicle in a vast parking lot, utilizing ambulance or taxi services at your closer proximity are few of the tracking and management service.

Other location based services: Location based services such as E - Billing, where the service provider dynamically charge the user for using the particular service depending on the location and augmented reality service, which pull graphics out of the phone or computer display and integrate them into real-world environments. In augmented reality, the user can see the real world around him, with computer graphics superimposed or composed with the real world. For example: The Massachusetts Institute of Technology (MIT) invented a device named Sixthsense, a wearable gestural interface that interconnects the physical world around us with digital information thereby allowing the use of natural hand gestures to interact with information of interest. Sixthsense seamlessly integrates the information with reality, and thus making the entire world your computer. For example, a newspaper can show live video news or dynamic information can be provided on a regular piece of paper. The gesture of drawing a circle on the user's wrist projects an analog watch.

1.3 Motivation and Scope of the Thesis

Recent advances in the field of mobile computing had led to indispensable trend towards indoor location based service equivalent to outdoor location based service. One such indoor location based service is pedestrian navigation. Indoor localization remains to be a potential approach for numerous applications in the commercial and public safety fields.

A handful of solutions had been employed to achieve pedestrian navigation. However, these solutions that are available in market either remained unreliable or highly expensive. The key criterion to achieve reliable navigation lies in instant and accurate localization of the user. For localization in an outdoor environment, GPS remains as an appropriate application. However, the signals received from the GPS based satellites cannot penetrate most buildings and materials. Although, one manages receive the GPS signal at indoors, the signal strength is not sufficient enough and remains a limiting factor for the performance of GPS. Hence GPS becomes totally ineffectual inside buildings. Indoor location based service and personal navigation is expected to remain as an innovative trend in the imminent future when all technological challenges had been shadowed.

Many schemes had been envisioned for indoor localization, mostly based on machine vision, range-finding, cell-network localization or fingerprinting and based on diverse technologies such as WLAN, Bluetooth, ZigBee, RFID and UWB. However, these schemes and technologies often do lack competent localization. Furthermore, these schemes linger either expensive or be deficient in accuracy. Moreover not all technologies exist in smart phones. The enabling of robust and accurate localization in harsh indoor environment faces real physical challenges such as multipath effects, insufficient signal coverage and non line - of - sight conditions.

The real challenge is to build a localization system that could face all the existing challenge for localization and be an efficient system to localize the user indoors. Recent outburst of technology expansion has paved way to solve indoor localization complexity by combining various positioning methods and sensor models. Although, the existing localization systems can improve the localization performance, they still face further physical limitations specific to the indoor environment. Some localization systems fail to be precise enough to serve some of the location based service. More importantly many localization systems have limited radio coverage which requires the establishment of connection with the new access points to continue the service. Other localization systems pose the question of reliability and flexibility. Few other localization systems fail to be cost efficient. The solution or an alternative is to design a system that could satisfy the criteria for localization and be a capable system that serves all the location based services.

The thesis, in particular demonstrates a prospect of achieving an efficient indoor localization in a cost efficient way by supplementing sensor technologies and its hybridization. Further, the described systems are validated in concurrence with specified criteria for localization. An optimized navigation algorithm is presented, which is able to provide the user with a quickest route to destination. The localization methods are proposed considering the multipath effects. Also, the experiments are carried over with different access point densities and at different environments and walking paths in a multi-storey building. However, the coordinate system is designed with a reference point in the building as the origin. It is a 3D coordinate system with the third coordinate indicates the floor number of the building instead of the height to the ground.

1.4 Contribution of the Thesis

In this thesis, an overview on the fundamental idea for localization and vital criteria needed for efficient localization is depicted and satisfied. The existing and the emerging technology of localization and their algorithms are discussed, highlighting the drawbacks in each approach in chapter 3. The research work focuses on four contributions to the field of indoor based wireless sensor localizations.

Analysis and measurements are made with the potential technology - Bluetooth to investigate the suitability of the technology for efficient localization in indoor multipath environment. This work presents empirical results of the measurement made on a pedestrian path in an indoor environment and projects the difficulties of this acquired technology in terms of localization.

These measurement results are considered and utilized to develop novel methods of localization such as multi-trilateration and fingerprinting. The analysis part is utilized to develop roaming algorithm to provide uninterrupted scaling of the system which Bluetooth technology lacks. The algorithm is presented in chapter 4.2 and the localization results are presented in chapter 5.2 and had been published in [41].

Investigations are made to find a reliable and precise solution for indoor localization with RFID. The measurements are made and the results are used to construct the sensor model based on tag detection which plays the role in estimating the position of the user. A novel approach combining tag detection count and the signal strength is used to localize the user. The algorithm is presented in chapter 4.3 with the results and a comparison to other approaches in chapter 5.3 and had been published in [42].

Cost efficient localization which can be obtained with the low cost inertial sensors is investigated. The work presents empirical results of the raw measurement data. These initial measurement results are used to develop novel methods of localization based on step detection and direction estimation [4.4]. The results of displacement and the direction travelled and the position estimated with its precision level is presented in chapter 5.4. The algorithm and the results are published in [45].

All these single sensor based solution lacks somewhere to be an efficient system for localization. Hybridization of the sensors is carried out with different combination of the above potential sensors. The methods, advantages and the drawbacks of the hybrid systems are presented in chapter 4.5. The comparison and a performance evaluation of the hybrid localization system to the single sensor localization systems based on the criteria for efficient localization is performed and the results are presented in chapter 5.5 and are published in [44].

An optimal navigation algorithm that can guide the user with utmost satisfaction in a multi-storey building and with better runtime is designed and presented in chapter 4.6.The algorithm takes into account the users preference and provides him the route accordingly. The runtime results of the navigation algorithm is presented and compared to some of the state of art approaches by testing it in the same environment. The results are published in [43].

1.5 Overview of the Thesis

Chapter 2 introduces some fundamentals of potential sensor technologies such as Bluetooth, RFID and Inertial sensor to develop an in-depth understanding of this functionality in these technologies for the indoor localization. It also briefs the filtering technique which is applied to all the proposed methodologies of localization to estimate the new position of the user based on the previous data and the received sensor measurement data.

Chapter 3 reviews the available methods in the current literature intensely existing in each of the proposed technologies for localization. The methods and their prospective pros and cons of the proposed approaches are described, weighed and analyzed. A comparison of these localization approaches to the proposed approaches in the thesis is pointed up. It also reviews the approaches that exist for navigation and addresses the advantage of the navigation approach proposed in this thesis in assessment to the state of art approaches

In chapter 4, the architecture for localization with potential sensor technologies and its hybridization is presented. The optimal methodology of localization designed by considering the key source of position errors is explained in explicit. The discussion on connectivity in networks and algorithm to enable the scalability of approaches are illustrated. It also details the optimal ways of guiding the user in the indoor environment with the proposed navigation algorithm.

Chapter 5 explains the experimental setup used for localization and provides the results of localization and navigation. The results about the precision of the proposed methods, reliability and the impact of the reducing the landmarks over precision is presented followed by the comparison to the state of art approaches. It also analyses and compares the results of all the proposed technologies to check the adaptability of these approaches for an efficient localization.

Chapter 6 reviews the suitability of the proposed technologies for different applications and thereby concluding the thesis with a summary and a future outlook.

2 Preliminaries

2.1 Methods of Localization

2.1.1 The Basic Localization Methods

The basic localization methods that provides the foundation to all novel localization algorithms are given below

Dead Reckoning : Dead reckoning (DR) is a method of estimating the user's current position based on a previous position, known speed, direction and the elapsed time. Modern inertial system depends on dead reckoning and is widely applied because of its low cost and complexity. However the positioning error accumulates over time and in addition starting position has to be specified to localize the user. Hence it is always used in combination with other sensor methods.

Proximity sensing or Cell Identification : Proximity sensing is the ability of a device to sense the object when it is in its immediacy. This method can be used to measure the distance between the sensing device and its opponent.

Trilateration : Trilateration is a method of determining intersection of three circles given the midpoint and radius of the circle. Trilateration is used with signal strength and the time of arrival (TOA) measurement. For instance, the distance between the transmitter and the receiver can be estimated from signal strength variation or absolute measurement of time of flight of the radio frequency emission. GPS receiver uses trilateration to determine its location from satellite data.

Multilateration : Multilateration, also known as hyperbolic positioning, is the process of locating an object by accurately computing the time difference of arrival (TDOA) of a signal emitted from that object to three or more receivers. It also refers to the case of locating a receiver by measuring the TDOA of a signal transmitted from three or more synchronized transmitters. Multilateration should not be baffled with trilateration, that uses distances or absolute measurements of time-of-flight from three or more sites, or with triangulation, which uses a baseline and at least two angles measured e.g. with receiver antenna diversity and phase comparison.

Triangulation : Triangulation is the process of determining the location of a point by measuring angles to it from known points at either end of a fixed baseline. The point can then be fixed as the third point of a triangle with one known side and two known angles.

2.1.2 Bayesian Filtering

2.1.2.1 Particle Filter

Particle filter [35],[7],[7] is a sequential Monte Carlo algorithm for tracking the variable of interest based on a non Gaussian and multimodal probability density function (pdf) over time. It is a sampling method for approximating a particle representation of the distribution that makes use of the temporal structure. The basis of the method is constructing a sample based representation of the entire pdf and a series of action based on the observation is carried over the variable of interest modifying its state according to some model.

The particle filter algorithm is recursive and is carried over in 5 steps as shown in the figure 2.1.

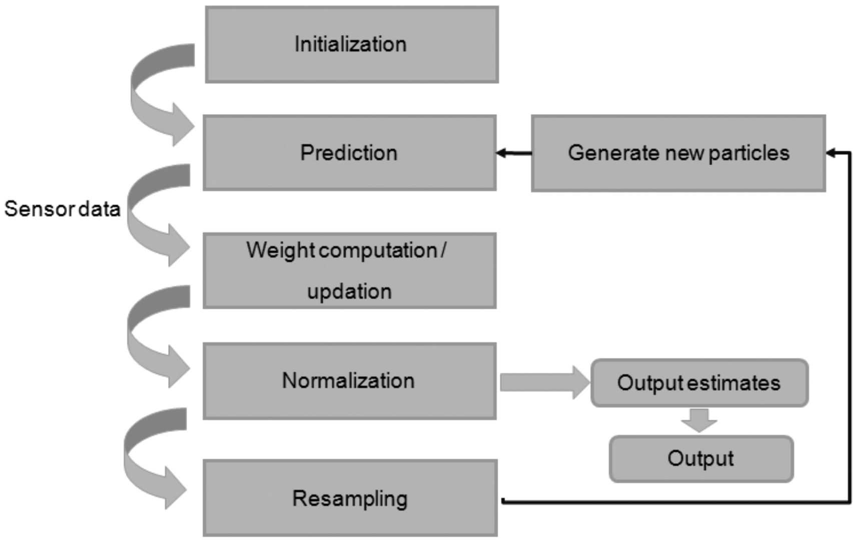

Abbildung 2.1: Principles of particle filter

Initialization : Multiple copies of the variable of interest i.e., particles, are drawn from the distribution each one assigned a weight that signifies the quality of the particle. The variable of interest at time t is x_k^t where $k = 1...n$ and n being the number of particles. Each particle is assigned weight w_k^t that defines the contribution of the particle to the overall variable estimate

Prediction : Each particle is modified according to the existing model including the addition of random noise in order to simulate the effect of noise over the variable of interest. In order to predict the probability distribution of the pose of the moving robot the effect of noise need to be modeled on the resulting pose. In our approach an additive Gaussian noise model for the motion is used as in the other approaches. The new pose $\left(X_k^{t+1}, Y_k^{t+1}\right)$ of the particle x_k^{t+1} is given by equation 2.1 and 2.2.

$$X_k^{t+1} = X_k^t + \alpha \tag{2.1}$$

$$Y_k^{t+1} = Y_k^t + \alpha \tag{2.2}$$

Where α is the Gaussian noise.

Weight Updation : Once the information from the sensor is received the particle weights are updated to estimate the new pose of the user. One of the method of updating is to estimate the probability of how far it is from the estimated pose of the object obtained from the sensory information s. Weight of each particle is updated based upon this previous weight and probability function $W\left(s, x_k^t\right)$. In the rest of the chapter, only the weight updation step based on the sensory information is explained.

$$w_k^{t+1} = w_k^t + W\left(s, x_k^t\right) \tag{2.3}$$

Normalization : The next step in the particle filter is normalization. The weights of the particles are normalized such that sum of the weight of all the particles is equal to one. The weight of each particle w_k^{t+1} is normalized according to equation 2.4

$$w_k^{t+1} = \frac{w_k^{t+1}}{\sum_{k=1}^{n} w_k^{t+1}} \tag{2.4}$$

Resampling: One of the problems that appear with the use of particle filters is the depletion of the population after few iterations. The particle that has smaller weights becomes too small to contribute the position estimate of the moving object. In such case particle with smaller weights are eliminated and the particles with higher weights are duplicated. If the set of particles x_k^t is considered as the discrete representation of the pdf of moving object then the new representation $x_l'^t$ is needed such that $x_k^t = x_l'^t$ with k and l in $[1, n]$ and the weight of $x_l'^t$ is such that $w_l'^t = \frac{1}{n}$ that represent the same pdf.

Three different methods are proposed to estimate the final pose of the object. The first method is the weighted mean first the weighted mean of all particles, second the best particle approach which considers only the particle with maximum weight and third the robust mean which computes the weighted mean out of the particles with maximum weight. Each method has its own advantages and disadvantages: the weighted mean fails when multimodal distributions occur, while the best particle introduces a discretization error. Robust mean is considered as the best method because it reduces the discretization error but it is most computationally expensive. In our approach the weight mean of all the particles is used to estimate the position of the object. The position P of the object is given by equation 2.5

$$P = \sum_{k=1}^{n} x^k w^k \tag{2.5}$$

2.2 Wireless Sensor Technologies

2.2.1 Bluetooth

Bluetooth a short range radio communication device that works on a wireless protocol is used for exchange of data between devices in a secured manner. Although Bluetooth was developed early in 1994, the Bluetooth Special Interest Group (SIG) formalized the entire design by the year 1998. The Bluetooth technology yet remains as a stupendous technology in the scientific and commercial world as they are readily available in all mobile devices, remain robust, compact and easy to use, are highly reliable. In addition when it comes to performance, they consume low power, quite flexible and reliable. Moreover, Bluetooth is boundless to all manufacturers.

2.2.1.1 Piconet and Scatternet

Bluetooth technology invented possibilities to allow a master device to connect equal to seven slave devices, thus forming an adhoc network called piconet. A master device or a slave device in a piconet can be active as a slave device in another Piconet.

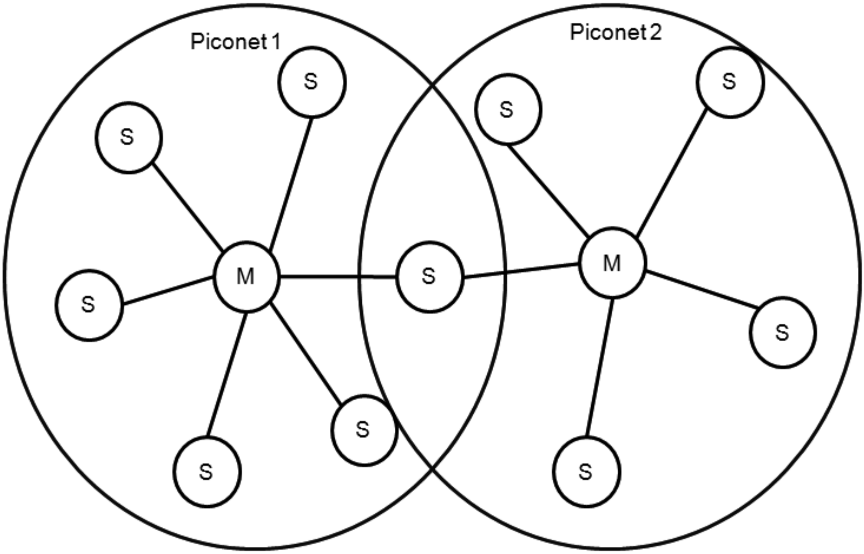

Abbildung 2.2: Piconet and scatternet

The same holds true for a slave device acting as a master in other piconet. This entitles a device can switch on either as a master or as a slave in a piconet.

A group of piconets are fused to form a scatternet. A scatternet is created when a master or a slave in one piconet link as a slave to a new piconet. The device participating in both piconets can relay data between members of both ad-hoc networks. The formation of the scatternet increases the physical size of the Bluetooth network beyond its range.

2.2.1.2 Frequency Spectrum

Bluetooth functions at an unlicensed ISM (The Industrial, Scientific and Medical) frequency at a band width of 2.4 GHZ (2400-2483.5 MHZ) and share similar frequency band for WLAN (802.11) as well. Both technologies utilize the spread spectrum modulation that leads to high vulnerability to interference. Bluetooth employs a frequency hopping spread spectrum signaling method (FHSS) to transmit radio signals. This is achieved by switching a carrier among several frequency channels, thereby utilizing a pseudorandom sequence recognized by both transmitter and receiver.

The frequency spectrum can be split as much as 79 radio frequency channels spaced 1 MHZ apart. Bluetooth can ably hop through all 79 RF channels and can avoid the interference. The hopping pattern is well devised in a way to exclude a portion of the frequencies used by interfering devices. The frequency of the hopping pattern is defined from the Bluetooth clock and the Bluetooth address of the master device in the piconet. All devices employed within the piconet are synchronized with time by means of the master clock, thereby updating the offset according to the master clock to that of their own clock.

2.2.1.3 Time Slots

The Bluetooth devices can transmit or receive the data in timeslot duration of 625μs. The master device uses even numbered slots to interact to the slave and the slave using odd numbered slots to reply. If the data couldn't be transmitted in 625μs duration, both master and the slave device has to linger for their next even and odd time slots. In addition, a few timeslots are used for broadcasts and as logical channels for synchronization and as control signals. The clock of the Master unit decides when these slots start and end, thus making slaves to be very closely synchronized to this clock.

2.2.1.4 Inquiry and Paging

Inquiry is termed in the sense of to discover the available devices in range. This inquiry procedure traces the Bluetooth addresses and the clock information in the available and accessible Bluetooth devices. The device invokes the inquiry procedure by broadcasting inquiry packets. The device that receives an inquiry packet replies by Frequency Hopping Synchronization (FHS) packet that holds the Bluetooth address and the clock of the device. Once the inquiry procedure is complete, a connection is established.

Paging is a specific term used for the procedure to establish a connection to other Bluetooth devices. For the paging procedure, the Bluetooth address serves as a prerequisite to establish a connection. In this context, there arises no necessity for an inquiry procedure persistently. Nevertheless, the information on the destination device clock provides an early paging procedure. The device that initiates the connection acts as a master of the connection.

2.2.1.5 Bluetooth Versions

Several specification versions were released by Bluetooth SIG after its launch. Bluetooth version 1.1 fixed errors found in Bluetooth version 1.0 and added support for non-encrypted channels. Version 1.1 has also included the Received Signal Strength Indicator (RSSI). The Bluetooth 1.2 version provided major development over previous versions in terms of faster connection and device discovery. This version also employed Adaptive frequency-hopping spread spectrum (AFH) to provide resistance to radio frequency interference with a higher transmission up to 721 Kbit/s.

Bluetooth 2.0 has an Enhanced Data Rate (EDR) for faster data transfer of about 3 megabits per second. Reduced complexity and low power consumption are added advantages in Bluetooth 2.0 version. Bluetooth 2.1 supplements Bluetooth 2.0 with extended inquiry response, sniff sub rating and with secure simple pairing (SSP). Bluetooth 3.0 version provides enhanced power control.

2.2.1.6 Bluetooth Power Classes

Bluetooth is primarily designed for low power consumption. The range is power class dependent and can be up to 100m, 10m and 1m. The Bluetooth devices can communicate reciprocally when they are in range. Bluetooth not necessarily has to be in the line of sight for communication between the devices. The table 2.1 below shows the range that could be obtained in each of the power classes.

Tabelle 2.1: Bluetooth power class

Class	Maximum power mW(dBm)	Approximate Range(m)
Class 1	100 mW(20 dBm)	100m
Class 2	2.5 mW(4 dBm)	10m
Class 3	1 mW(0 dBm)	1m

2.2.1.7 Bluetooth Roaming

There are two major limitations of Bluetooth. First, the communication between the Bluetooth devices should be direct and is limited by the quality of service of the channel. Secondly, the automatic handover of active connection from one device to the other is not yet defined. Essentially in Bluetooth, there is no profile specified that defines how the seamless roaming can be performed that in turn enables intersecting piconets to communicate.

2.2.2 RFID

Radio Frequency Identification (RFID) in general, is defined as an automatic identification technology that uses radio waves to transmit the identity of an object or a person in a wireless mode by incorporating a small electronic chip on to the host. RFID is basically based on wireless communication protocol, utilizing radio waves that form part of the electromagnetic spectrum. The RFID operate with different frequencies in different countries. For Instance: Europe uses the operating frequency of 868.2-868.8 MHz, whereas North and South America uses operating frequency of 902-916 MHz. The operating frequencies are organized as four frequency bands : Low frequency (LF), High frequency (HF), Ultra High frequency (UHF) and finally as a microwave.

Tabelle 2.2: RFID frequency spectrum

Name	LF	HF	UHF	Microwave
RFID frequencies	125-134 kHz	13.56 MHz	865-956 MHz	2.45 GHz
Reading range	0.5m	1.5m	0.5-5m	10m

2.2.2.1 Components of RFID

A basic RFID system consist of three components

1. RFID Transponder or Tag
2. RFID Reader
3. System that uses the data from the reader

RFID Transponder or Tag: RFID transponder, commonly acknowledged as RFID tags is a unique type of microchip that transmits and receives data using radio waves. Most RFID tags contain at least two parts. The first is an integrated circuit, employed for storing and processing information, modulating and demodulating a radio-frequency (RF) signal, and for specialized functions. The second is an antenna that receives and transmits the signal. The tag stores diminutive amount of

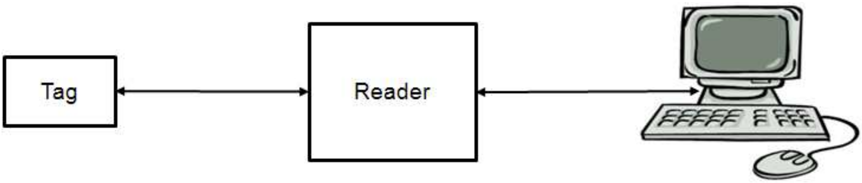

Abbildung 2.3: Components of RFID

information such as unique serial number called Tag ID. When the reader interrogates the tag, it returns back the tag ID to the reader. RFID tags vary widely in size, shape and color.

Types of RFID tags : Three types of RFID tags are available: Active tags, Passive tags and Semi active tags.

Active tags: Active tags include replaceable or sealed batteries which provide the power source to the circuit and the antenna facilitates the signal transmission on its own. A reading distance of one 100m or more can be well achieved by UHF active tags. The downside is that it needs a power source such as battery. The tag as well as the maintenance cost makes these tags unsuitable for much applications. Active tags can provide memories as high as 128 kilobytes.

Passive tags: Readers provide the power source in case of passive tags. Passive tags do not encompass battery; rather it acquires adequate energy from the RF field generated by the reader. To transmit data, passive tags apply Back scatter technology that reflects the readers signal, thereby modulating the signal to transmit data. The coiled antenna provided make use of the radio waves received from the reader leading to induced magnetic field to power the circuit in the tag. The tag is thus capable of routing the identity encoded on the respective tags. Although passive tags remain inexpensive, tags cannot be employed for a longer range. A UHF passive tag has a reading distance of 10m. Passive tags typically have somewhere from 64 bits to 1 kilobyte of non-volatile memory.

Semi-passive tags: Semi-passive RFID utilizes an internal power source to monitor environmental setting, but requires adequate energy from the RF field generated by the reader as of passive tags. Hence it offers a very good range of readability. They remain fragile and are short lived but reliable compared to the passive tags, and notably more expensive.

Tag memory : Tag memories are separated as four distinct banks: Reserved memory, EPC (Electronic product code) memory, TID (Tag Identity) memory and a user memory. Reserved memory contains the access or kill password, whereas the EPC memory contains the CRC and EPC information. TID memory possesses the unique identity of the tag. Figure 2.4 shows the logical memory map of the tag.

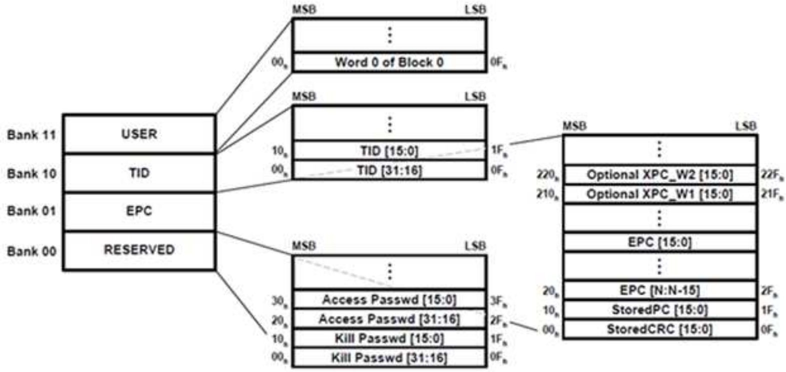

Abbildung 2.4: Memory banks of RFID tag

RFID reader: An RFID reader is a handheld device implemented to interrogate an RFID tag to acquire their unique IDs based on the radio frequency communication. The reader's antenna emits radio waves backscattered by the passive RFID tag, thus sending back its data. The reading range of the reader can vary from 1 inch to 100 feet depending on the output power and the radio frequency used by the reader. A number of factors can influence the reading range of the reader such as frequency used, the orientation and polarization, the transponder antenna, the antenna gain of the reader or the mode of tags placed on the objects. Occasionally tag collision occurs, when one or more than one transponder reflects back a signal at the identical time thus puzzling the reader.

RFID readers may take advantage of anti-collision algorithms developed by different firms to singulate the tags thereby enabling a single reader to read more tags in the reader's field. There are two main classes of RFID readers: read-only and read write. Read only set of readers operate with the passive EPC Class 1 tags, whereas read/write set of readers in addition to reading the tag information, can also write new information back to a tag that has been equipped with a read/write memory. The readers available these days are becoming increasingly sophisticated by supporting wireless communication protocols such as WLAN and Bluetooth. Today's readers can be integrated well into handheld devices such as PDAs and mobile phones [5],[3].

System: The system is the device which utilizes the interrogated data from the RFID reader to build an application. Unique tag ID, EPC, CRC read from the tag are sent to the system for processing by the RFID reader. The transfer can be achieved either using wired or wireless protocol.

2.2.2.2 Tag Operations

Various operations can be executed on the tag by the reader. Some basic operations that can be employed by the tag are

Inventory : Inventory is defined as a process by which a reader recognizes tags. The reader begins an inventory round by transmitting a query command in one of four sessions. One or more tags may respond. The reader detects and replies to a single tag and requests the PC word, optional XPC word or words, EPC, and CRC-16 from the tag. An inventory round operates in one and only one session at a time.

Read : The reader is capable of reading the data from a specific memory bank unless the data is not key protected. The reader issues the read command with the parameters: memory bank and the memory location to the tag. The tag in turn returns the data stored at the particular memory location of the corresponding memory bank.

Write : The reader can write the data to a specific memory location in the memory bank, condition that the tag is write enabled. The reader issues the write command with the data to be written and the memory location and the memory bank to which it has to be written. The tag stores the data in the particular memory bank in the specified location.

2.2.3 Inertial System

An Inertial system is composed of module with accelerometers and a compass or gyroscope or other motion-sensing devices and the user interface provided with the computer. An inertial system can ably detect a displacement or modification in varying velocity and the orientation of the user and computes an updated position of the user who carries the device. Initial position is acquired from sources such as GPS or wireless sensors (Bluetooth, RFID). It is also termed as Dead reckoning system as it can estimate a user's position using various other factors such as earlier position and displacement (measuring the acceleration), velocity and the direction (measuring the orientation) obtained from other sources. This may lead to accumulation of errors when the system is scaled. However, the advantage of an inertial sensor is that it requires no external references to determine its position, orientation, or velocity once initialized. Moreover, the reduced cost and complexity of the system makes it best suitable for many applications.

Acceleration is defined as change in velocity over time [Figure 2.5]. Accelerometers measure the linear acceleration along the three axis in the inertial reference frame. Integration of the linear acceleration results in the inertial velocities of the system and integrating again results in the inertial position. The accelerometers are not aware of their own orientation. They are fixed and rotate with the system. Hence, the direction can be measured relative to the moving system. At any point on a trajectory, the magnitude of the acceleration is given by the rate of change of velocity in both magnitude and direction at that point. The true acceleration at time t is found in the limit as time interval $\Delta_t = 0$.

Gyroscopes comprise essentially a spinning wheel or a disk whose axle is free to take any direction. Gyroscope measure the angular velocity of the system in the inertial reference frame. Integrating the angular velocity and with the original orientation of the system as the reference, the system's current orientation can be computed all the time.

A compass determines the direction of the system relative to the Earth's magnetic poles. The compass comprises of a magnetized pointer which is liberated to line up with Earth's magnetic field. A compass can be used to calculate heading. A gyrocompass is a compass that finds true north by using a fast-spinning wheel and friction forces in order to exploit the rotation of the Earth.

All inertial navigation systems suffer from integration drift; small errors in the measurement of acceleration and angular velocity are integrated into progressively larger errors in velocity, which is compounded into still greater errors in position. Since the new position is calculated from the previous calculated position and the measured acceleration and angular velocity, these errors are cumulative and increase at a rate roughly proportional to the time since the initial position was input. Therefore the position must be periodically corrected by input from some other type of navigation system.

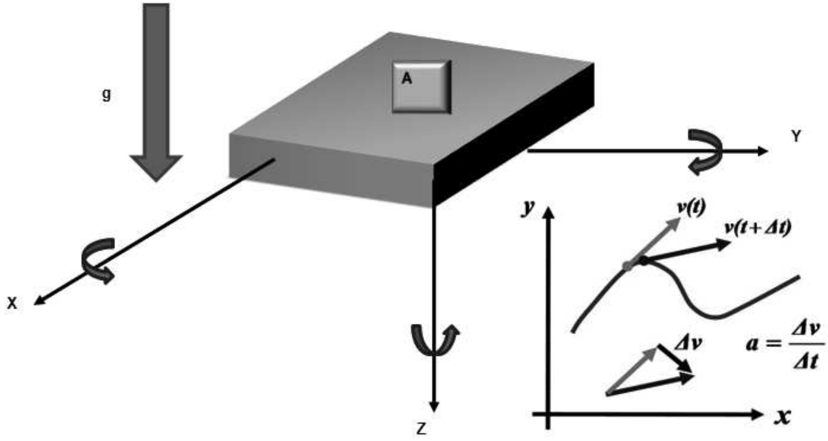

Abbildung 2.5: Inertial system

2.3 Classification of Localization based Systems

Localization-Based Systems can be broadly classified as three categories. Network based positioning, Device based positioning and Hybrid positioning.

Network based positioning : Network based positioning utilizes the base station network infrastructure to identify and track the mobile device location. The advantage of network based positioning is that they can be operational independent of the mobile device. The accuracy depends on the number of base stations and the technique employed for localization. With Cell identification technique the accuracy will be poorer whereas with triangulation an improved performance and accuracy can be foreseen.

Device based positioning : In device based systems, the client software needed to be prior installed in the mobile device to determine the location. The location of the device is calculated either by cell identification or signal strength based on the signals from the base stations. The position estimated at the mobile device is then sent to the location server to provide the location based service. Since the software needs to be installed in the mobile, it threatens the privacy of the mobile device.

Hybrid : Hybrid positioning systems use a combination of network-based and device-based positioning for location determination. One example would be Assisted GPS, which uses both GPS and network information to compute the location. Hybrid-based techniques provide the best accuracy of the three but inherit its own limitations and challenges of network-based and handset-based technologies.

3 State of the Art

Various existing wireless technologies successfully employed for indoor localization are described in literature.

The Active Badge System [55] realizes indoor positioning by means of IR. Active Badge emits pulse-width modulated infrared signals which are picked up by a network of sensors placed around the host building. There are two major limitations that make it not much effective for indoor location sensing. Firstly, infrared uses only short range signal transmission and secondly it requires Line-of-sight for sender and receiver.

The Bat Location system use the ultrasonic ranging to provides fine-grained 3D location. The distance is estimated using the time of flight measurement from the beacons and the position is estimated using trilateration. The accuracy of the system is around 3cm in three dimensions. The Cricket Location Support System [34] includes the use of beacons with combined RF and ultrasound signals in a decentralized, uncoordinated architecture. It uses independent, randomized transmission schedules for its beacons and a receiver decoding algorithm that uses the minimum of modes from different beacons to compute a maximum likelihood estimate of location. The accuracy of the system is to a few centimeters and the angle is within 3-5 degrees of the true value. Depending on the density of infrastructure and degree of calibration, ultrasonic systems have accuracies between a few meters and a few centimeters.

RADAR [8] is a radio-frequency (RF) based system for locating and tracking users inside buildings using WLAN technology and is based on empirical signal strength measurements as well as effective signal propagation model. While the empirical method is superior in terms of accuracy, the signal propagation method makes deployment easier. In general till to date, the overall accuracy of the systems, using WLAN technologies, are not as precise and optimal as desired. For instance, the median resolution of the RADAR system is in the range of 2 to 3m, with 50% probability, while the signal strength lateration implementation has 4.3m accuracy at the same probability level.

Another accurate indoor GSM-based localization is possible with the use of wide signal-strength fingerprints that include readings of up to 29 GSM channels in addition to the 6-strongest cells. GSM-based indoor localization system [50] achieves a median accuracy ranging from 1.94 to 4.07m.

Another Indoor Localization System based on the ZigBee Standard [46] estimates the distance between sensor nodes by measuring the received signal strength indicator (RSSI) and position estimation techniques. In most cases to date, the accuracy achievable by using ZigBee depends on the deployment density of the sensor nodes. When the installation density of sensor nodes was set to 0.27 nodes/m^2, the position estimation error could be reduced to 1.5-2m.

UWB technology is the best option for very precise location estimation due to its high resolution capability in the time domain and its ability to resolve multipath components. The system provides sub centimeter accuracy. However, the system is not cost efficient.

Although, many technologies were proposed for Indoor localization all technologies have their own advantage and disadvantages. Active Badge, BAT and CRICKET system requires a line of sight condition, the RADAR is not reliable and is not very accurate, the accuracy of Zigbee depends on the density of the node installed and UWB is not cost efficient. Considering the criteria for localization, three augmented technologies (Bluetooth, RFID and MEMS sensor) and its methods of localization that exist in the literature are reviewed further.

3.1 Existing Bluetooth Systems

In this section, localization systems based on Bluetooth technology that exist in the literature is described.

The localization system proposed by Bargh et.al [10] is based on the Bluetooth fingerprinting approach. Fingerprinting relies on inquiry response rate of Bluetooth technology. The system is able to estimate the position of the target device using the Kullback-Leibler function and the Jensen-Shannon distance measure. The localization method works with inquiry response rate and hence doesn't require any connectivity to the Bluetooth beacons. Moreover the system doesn't require any installation of the software in the target device and hence it supports the privacy of the user. The localization system requires the target device to be stationary for 3 minutes and claims to provide an accuracy of 98% in rooms with full Bluetooth sensor coverage and 75% in rooms with partial Bluetooth sensor coverage respectively.

The indoor positioning system presented in [14] is based on the signal strength measurement approximated by the received RSSI of the mobile device. The method used for localization is triangulation and the least square estimation. The range estimation of the positioning system is based on an approximation of the relation between the RSSI (Radio Signal Strength Indicator) and the associated distance between sender and receiver. The localization system provides an accuracy of 2.08m given the distance of less than 8m between the access points and the mobile device.

Fischer et al. [15] presented a Bluetooth indoor localization system, where the position of the user is determined by differential time difference of arrival measurements (DTOA) utilizing a dedicated cross correlation IC. The correlation IC performs a cross correlation of the receiving signal in real time with a previously stored pseudo-random (PN) reference code to determine the exact receive time. There need not be time synchronization between the clocks of the measuring beacons. The target device requires no additional hardware or software to be installed. However, the localization system requires a line of sight between the beacons. The localization system provides an accuracy of 1m.

The localization system presented in [56] is based on the signal strength of the established Bluetooth connections determined by the RSSI and transmit power of the connection. The localization method is based on conditional probability created from the transmit power levels and the RSSI values. However, the achievable accuracy depends on the number of beacons used for the localization setup. The system can achieve an accuracy level of 2m with a standard deviation of 1.2m.

A particle filter based localization approach to estimate the position of the user is presented in [53]. The position of the target device is calculated by estimating the gaussian likelihood function that depicts how well the distance between the particle and the Bluetooth beacons, computed from the RSSI-based distance estimates. This particle filter solution provides a robust indoor positioning system for medium range distances with an accuracy of 50cm with a standard deviation of 0.14m.

The localization system described in [60] make use of RSSI in a novel way. The distance was estimated between a target device and the installed Bluetooth beacons, using a line-of-sight radio propagation model within a single cell. The system provides a mean absolute range error of 1.2m was feasible in the presence of multipath fading.

The localization system presented in [23] implements Bluetooth Local Positioning Application (BLPA) on the HCI layer. Location estimation is based on distance estimated from received power levels according to a simple propagation model. The extended Kalman filter computes 3D position estimate on the basis of distance estimates. The mean absolute error of positioning measured by the system is 3.76m. However, the accuracy can be improved if Bluetooth devices are able to measure received power levels more precisely.

The system presented above requires high density of sensors to provide the presented accuracy. The Ambient system presented in [20] attempts to reduce the number of sensors needed in a Bluetooth-based network for indoor location determination while maintaining a comparable accuracy to the full network. The localization is based on reference fingerprint based on inquiry response rate of the Bluetooth device. The system uses the entropy sort optimizer and the worst contributor removal optimizer algorithms which optimizes the number of active Bluetooth sensors, targeting a certain localization accuracy level. The system provides an accuracy of 0.95m retaining 55% and 65% of the devices. However, the system endures the scalability issue and it is difficult to maintain fingerprint originality at an acceptable level.

3.1.1 Existing Bluetooth Roaming Methods

Many proposals were done in the area of Bluetooth Roaming. One of the approaches [59] describes the implementation of an extra layer (Relay Layer) between L2CAP and its higher layers to do roaming. Another approach [30] does the roaming with the concept of service name. These approaches failed to provide uninterrupted service, which is the base for roaming.

3.2 Existing RFID Systems

Indoor positioning using RFID technology has been studied to a great extent especially for robots and pedestrians.

In one approach utilizes super-distributed smart-entity infrastructures for tracking objects in indoors [37]. The prototype reveals that the positioning service provides an average accuracy of approximately 15cm at a meticulous walking speed with a tag density of 39 tags/m^2.

Wilson illustrates that received signal strength information between the reader and the tagged item need not be a factor to localize the objects, whereby they designed a method that maps the tag count percentage to the database of tag count patterns at various attenuation levels and distances from the base station reader [58]. The tag count results measured during the runtime is compared with the characteristic curve of different tags in the database using a derivation of Euclidean distance. The method shows the feasibility of tag count percentage based method to localize the user.

SpotON [18] is a well-known three dimensional location sensing system that makes use of received signal strength indication (RSSI) to estimate the distance between the active RFID tags and thereby localizing the user with the help of inter-tag distance. The location of the user is computed by the straightforward hill-climbing aggregation algorithm which attempts to minimize signal strength error relative to empirical data. The radios used in this approach can handle hardware variability, hence increases estimation accuracy.

The LANDMARC [30] approach utilizes reference tags to localize an object indoors. The localization method scans the power level of the tags to estimate its signal strength. Euclidian distance is computed between the signal strength of the reference tag and the tracking tag. The location of the user is assumed to be the reference tags location which has smaller euclidian difference. However, LANDMARC has drawbacks such as ample scanning time to scan all the power levels, dependence of accuracy on tags behavior and long latency for every update as computation is executed in a server.

Haehnel attained indoor localization using RFID and laser scans [32]. In this approach, a probabilistic sensor model was used to compute the likelihood of tag detections given the pose of the tag. First the map of the environment is generated environment using a laser range sensor. Then the position of the tag is estimated based on the path generated by the robot. Given this map and the maximum likelihood path computed by the Fast SLAM algorithm the position of the RFID tags are computed using recursive Bayesian filtering scheme. The downside of this approach is that it does not work independently without the input from the laser scans. The approach claims to have an average accuracy of approximately 1m.

The Snapshot approach uses the idea of vision based localization and the tag detection for localization [39]. The algorithm features a particle filter for localization, utilizing the detection rate of tags obtained from snapshots and the odometer data from the robot. An accuracy of 40cm is achieved after few executions of the particle filter. The drawback of this approach is the time-consuming training phase as it requires several snapshots to be done earlier, and accurate self-localization is possible if there are reference snapshots.

Ferret presented in [27] is a RFID based scalable system for locating. The system uses an online algorithm for real-time use on a mobile device, and an offline algorithm for use in post-processing applications. Ferret initializes a three dimensional map once it receives the positive reading of the tag and uses the coverage map, to track the probability that the object is at each of the coordinates in the map. Hence it multiplies the coordinate of the coverage map with the coordinate of three dimensional maps if the reading was positive. With the online algorithm, instead of using a map of probabilities for the coverage map, the convex shape that describes the coverage region of the RFID reader is reduced from the coverage map. Ferret can refine object locations to only 1% of the reader's coverage region in less than 2 minutes with small error rate (2.22%), Ferret can detect nomadic objects with 100% accuracy when the moving distances exceed 20cm. Ferret can use a variety of user mobility patterns.

The system presented in [57] is based on active long range RFID system which collects RSS values from various RFID tags in the environment. The position is calculated using particle filtering algorithms. In the calibration phase few tags were installed in representative locations and then measure the RSS distribution and non-detection rate for certain distances around each tag. The total data set is aggregated to yield the distribution of the RSS value over average distance from our RFIDs. The Likelihood that the tag could yield the particular distribution of RSS value is used to update the weights of the particle. The system is able to provide an accuracy level of 2.2m.

The localization system presented in [14] estimate the position of the user using cooperating landmarks that provide the ability to measure range only. If the positions of the landmarks are known, measurements from multiple landmarks can be combined using probability grids to provide an accurate estimate of location. This estimate can be improved by using Monte Carlo techniques and Kalman filters to incorporate odometry data.

A cost saving, robust localization method for precise indoor positioning utilizing Radio Frequency Identification (RFID) technology is presented in [26]. Reading patterns of the RFID tags at each location as collected and a pattern recognition and classification method is used to estimate its location of the user. The resulting estimation error is within one meter. The method is adaptive to different tag distributions, reader ranges, tag reading defects, and other alterable physical constraints.

The localization system presented in [48] introduces a multiscan based sensor model that can be learned in online, and then integrated the robust sensor model within the framework of SGD map optimization. The proposed method clearly outperforms the conventional ones in convergence performance as well as accuracy. The system is able to deliver an accuracy of 2m.

The system proposed in [49] improves the localization accuracy of short range RFID reader. The method is based on machine learning approach in which multiple classifiers are trained to distinguish RFID-signal features of each location. The tag arrangement is recommended automatically by the system. The effectiveness of the proposed technique is evaluated experimentally with a real mobile robot and an RFID system.

3.3 Existing Pedestrian Dead Reckoning Systems

While researching possibilities for indoor localization has been a (still) continuing effort, research has intensified on the field of error correction via filtering. However, when cost is the factor, IMU is the best solution for indoor localization. When combined with other sensor technologies, it can be an efficient indoor localization system.

Schindler et al [38] used a combination of a proximity sensor and a dual-axis accelerometer. The Free Digitizer device detects doorways and builds a map out of this information while the IMU is used to detect footsteps. A particle filter then combines this information to track the user within the built map. The IMU is head-mounted with the proximity sensor. In their work Schindler et al take the x-axis acceleration into account which in their case is an acceleration perpendicular to the direction the user is walking. They use a pattern-recognition approach of zero-crossing of the low-pass filtered x-axis acceleration to detect a step. However, this approach proved to be faulty during the experimental phase as slight movement of the sensor caused the raw values to not zero cross at all during a step occurrence or multiple times which lead to wrong step-detection. This system identified 408 out of 418 steps with an accuracy of 97 %.

Popa et al [33] used a combination of the Cricket system and an INS. The Cricket system needs a Line-of-Sight environment to compute a user's position between the Cricket nodes and the user - more precisely between the listener and the mote. Therefore an INS consisting of an accelerometer and a gyroscope was added to the system. Location estimation with the INS is implemented by integration of the measured velocity over time. This is of course due to accumulation of errors exponentially with the sensor already has a drift error in its measurements and these values are integrated twice to compute the user's location. The system can attain an accuracy of 90cm when combined

Wang et al [54] designed a WLAN-based pedestrian tracking system in combination with a MEMS INS. To improve the WLAN-based tracking information they used a particle filter and a low-cost 3-axis MEMS accelerometer. For the accelerometer-based localization they used a zero-crossing algorithm. Though the WLAN-based tracking could be improved with this system, the MEMS localization proved to be error prone. However, performance improvement of 25% can be reached when using the combined framework compared to results obtained using only WLAN based positioning.

Renaudin et al [36] introduced a hybrid system of MEMS INS and Assisted GPS to improve personal tracking. They joined the information from the INS and the AGPS with a Kalman Filter and different stochastic models. Their system proved to be accurate up to 0.93m in an outdoor environment. The deviation from the original path grows of course when changing from an outdoor to a light indoor or indoor environment. However, they use integration to compute the user's position out of the INS values which leads to accumulated errors over time.

Ojeda and Borenstein [31] introduced a personal dead-reckoning system for GPS-denied environment (e.g. an indoor environment). They attached an IMU at the user's boot to detect a footstep. The user's position was computed by double integrating the acceleration values over time. They met the problem of error accumulation over time by introducing a Zero Velocity Update (ZUPT). During the rest phase between two steps they reset the velocity error to a primarily known zero condition to compute the velocity and location for the next step with less offset drift induced error. Their system reached an error of 2% of distance travelled over a short period of time. Still they use the computationally expensive double integration of the data.

Kleiner [21] used an Xsens IMU with 3-axis-accelerometer and 3-axis-gyrometer to update the odometry data of his robot. He used a PDR approach similar to Ladetto et al [24]. A step corresponds to a local maximum when the heel impacts with the floor. To detect the frequency of steps, the maxima in the acceleration curve are counted. Further a low-pass filter is applied to the acceleration data to avoid counting maxima that are induced by the impact of the sole with the ground. The travelled distance is then obtained by multiplying the step frequency with the step length. Kleiner and Ladetto et al distinguish between forward, backward and side-wards movement. This algorithm results in a good distance and position estimation depending on the step length. Ladetto et al calculate the length to an average of 0.75m and Kleiner refines it by using Global Navigation Satellite System (GNSS) positions.

Bancroft [9] presents a Twin IMU Integration Scheme where he uses two IMUs with accelerometer and gyro sensors. He updates the IMUs with each other and uses tight integration, several filter methods and ZUPT to get acceptable location estimations. However, the system still uses integration with its problems and needs a lot of computational power to clean the location values.

3.4 Existing Hybrid Systems

Indoor localization systems using hybrid sensors and wireless technologies were studied extensively and described to a great extent in literature over a decade. In one approach using RFID, Decentralized slam (DSLAM) algorithm is employed for sharing information between pedestrians in an altruistic manner [22]. Also in this approach, the PDR (Pedestrian Dead Reckoning) method is used to track automatically the position of each pedestrian from acceleration patterns. In a nutshell, based on shared information history, RFID provides optimization to accelerometer values for tracking individual's path. Miyaki et.al [29] presented an object tracking scheme by fusing sensors (WLAN and the camera). The visual information from cameras and location information based on RSSI input from WLAN are fused together in a particle filter to track the target in a stable manner. This approach can cover wider areas both indoor and outdoor with low cost.

Conaire1 et.al [12] showed that both image-based and RF based systems can exhibit robust performance in localization, even with erroneous data. As pairing sources of data, the fusion of the two approaches improves performance, leading to considerable increases in accuracy of 0.26m.

Gwon et al [17] presented a localization system fusing information from multiple wireless technologies (WLAN and Bluetooth). They proposed and validated two location algorithms, Selective Fusion Location Estimation (SELFLOC) and Region of Confidence (RoC), which can be used in conjunction with classical location algorithms such as triangulation, or with other location estimation systems. SELFLOC fuses the data from multiple technologies in an optimal manner whereas RoC overcomes the problem of aliasing. The mean accuracy of the SELFLOC algorithm is 1.6m. However, when the user is mobile RoC helps the system to reach the accuracy of 3.7m.

Hossain et.al [28] presented a robust localization system combining WLAN and Bluetooth. They presented results of two localization algorithms (K-Nearest Neighbor and Bayesian Probabilistic Model) experimenting the same with both the wireless technologies. They achieved an average accuracy of 3m. The system presented reduces training time and is flexible

J. A. Corrales [13], presented a hybrid system combining IMU and UWB using kalman filter. The position of the user is computed from the measurement from the inertial motion capture system which registers full-body movements of a user. However, Ultra-Wideband (UWB) technology is used to correct the errors returned by the IMU. A Kalman filter fusion algorithm fuses both the measurements to estimate the position of the user. The accuracy of the system is 0.14m

GRIPS system [47] is a hybridization of different sensor technologies like Bluetooth, RFID, WLAN, Zigbee, and WiMax. The algorithm uses the signal strength measurement from all these sensors to localize the person based on mass spring model, atomic multilateration as well as Kalman-filter enhanced atomic multilateration. A

GRIP does not require any extensive environmental signal strength profiling.

RAPOSI [40] integrates several wireless technologies, namely WLAN, Bluetooth and RFID. The positioning is based on a radio propagation-model, by mapping radio-signal strength measurements to distances. The system's overall tracking accuracy is 2m. However, the spot-on short-range RFID-tag based tagging accuracy is about 50cm.

3.5 Existing Navigation Systems

Indoor positioning and navigation had been widely studied to a greater extent especially in robots and pedestrians.

Pierre-Yves et al., [16] presented the development and the implementation of navigation algorithms to access map databases by a user equipped with a pedestrian navigation system. The navigation algorithm works by building a 3D topological model of the infrastructure followed by the map-matching routines. The classical methods developed to find optimum paths through networks, such as the shortest path algorithm (Dijkstra), are based on link/node structures. A dedicated map-matching algorithm which processes the combination of the position data with the map database enhances the performance of the system. The system claims to be more robust.

In approach [51] the navigation scheme is supplemented with user profiles and with adoption of an ontological framework. They presented the issue of semantic location based service and presented a k shortest path algorithm. This proposed approach that had been designed for navigation services, directly involves many human aspects. The runtime of the k shortest path algorithm was 903.1ms with the total response time of 3513.9ms when executed in Intel Pentium 4 (3 GHz) processor running Windows 2000 server operating system. For navigating between floors, kSP algorithm calculates the path from the current position to all the floor exits then finds the path between floor exits and finally calculates the path from the destination floor exit to the destination point.

Vlassis et al [52] describe a novel global path planning method which operates on top of a qualitative map of global topology of the environment. The approach uses a modified version of the Dijkstra's shortest path algorithm that takes into consideration the curvature of the trajectory and the off -wall distance of the map points. The algorithm applies a set of criteria that can minimize the errors in the navigational accuracy and computes in real-time a set of optimal paths for reaching the destination

The path planning algorithm described in [59] uses the A* and Dijkstra's shortest path algorithms and operates on an intelligent map. The map is based on the data structure predicated on the relationships between the different objects that represent an indoor environment. The average position deviation error of the computed prediction was 69.7 and 54cm when the positioning accuracy was 300cm and 120cm accuracy respectively.

3DPLAN [11] is the three dimensional route planner that uses the A* algorithm to find optimum paths employing the new mobility and threat heuristic. Although the computational cost of using A* for 3D route planning is too expensive new heuristics substantially speed up the A* algorithm so that the run times are quite reasonable. The 3DPLAN route planner is 4.3 times faster, compared to straight line mobility heuristic and no threat heuristic.

The path planning algorithm presented in [19] starts with the map building of the completely unknown environment based on the multi-agent platform, and completes with AEF calculating and the path planning. However, the complexity of the algorithm is high. The solution [25] proposed to complex dynamic path planning problems is the anytime Dynamic A*, a heuristic-based, anytime replanning algorithm. The algorithm uses the previous searches thereby increases the optimality of the solution.

3.6 Conclusion

Existing sensor technologies and their localization potential have been evaluated in explicit in the literature review. Although few of these technologies seem to be promising for localization, in one way or the other they lack attributes such as accuracy, robustness and flexibility. Most of them yet remain expensive. The localization should remain applicable to all types of indoor location based services, which today's localization system fails to accomplish. Few prerequisites have to be met for efficient indoor localization:

Reliability: defined as consistent performance of the device to provide accurate location of the user and remains operational over time. Reliability is measured as the percentage of accuracy of the system over specified interval of time.

Accuracy: is the extent of proximity of localization measurements to its actual value. Accuracy is calculated or measured in terms of worst, average and best proximity of the localization system.

Scalability: defined as the ability of the system to provide uninterrupted service when network is being enlarged. In brief: it refers to the service availability regardless of network expansion.

Robustness: is the extent of coping well with added or floating variations (such as obstacles) in an operating environment with no loss of functionality. A system is said to be robust if it performs well despite abnormalities.

Performance: is the response of a system to execute any operation within a certain interval of time. Performance is measured in terms of latency. Latency is the time taken to perform a specific operation.

Flexibility: the ability of a system to adjust to changing or new environments. A flexible system can easily be reconfigured or adapted to location responses and system requirements.

Availability: is the ability of the normal users to access the localization system without any additional hardware at any environment.

Cost efficiency: The cost to build up an efficient localization system is calculated from the cost of the hardware and the environmental setup.

Routing: Some location based services need routers in an environment. For instance these routers aid in transferring data among users within the same location. This can be well achieved by updating the location of each user to the router over time.

One of the main research objectives is to invent a localization system that should accomplish factors in a satisfactory manner and could be easily customized to any indoor location based service. Unfortunately most of the existing algorithms did not consider the impact of environment and the people and have not succeeded to address the means to achieve improved performance. However, these systems provided a baseline to localize the user in indoor environment.

The Bluetooth based localization proposed in this thesis, uses the fingerprinting method as in approach [53] and the user¥s position is estimated with the particle filter. The system is able to provide the uninterrupted service for 80% of times using the proposed roaming algorithm which approaches [30] and [59] fails to provide. Moreover the system is able to provide an accuracy of 1m when high density of Bluetooth nodes are installed, which is better when compared to the systems [10], [14], [56], [60], [23].

The RFID based localization proposed in this thesis, uses the likelihood of tag detection as in Haehnel's approach [32]. However, by using only parameter tag count one cannot achieve reliable indoor localization as it leads to false positive results. Also one cannot rely on attenuation all times. Unlike from the reviewed approaches [15] to [53], the design takes into account the tag RSSI as well as tag detection rate that yields accuracy of 35cm in the worst case. Moreover, a training phase as in approach [53] is not necessary that consumes ample time. The RFID based approach in this thesis attained an efficient localization outcome even when reduced distribution of tags (15/m^2) is used compared to a distribution of 39 tags/m^2 as discussed in approach [14]. Overall, using this design one can obtain an efficient, reliable, scalable, cost-effective indoor localization system.

The PDR approach proposed in this thesis, uses a pattern-recognition scheme similar to zero crossing or the counting of maxima by Ladetto et al [24]. However, the proposed system overcomes the problem of sensor movement and doesn't need a sophisticated filter method to detect a step. With the proposed system more than 90% of the step occurrences are detected and are easily computed to a traveled distance and location estimation with the orientation values of the low-cost MEMS sensor.

In this thesis, a hybrid localization approach combining the three sensors technologies MEMS sensor, Bluetooth and RFID is proposed. The employed algorithm using the MEMS sensor and Bluetooth data localizes the user. It utilizes the RFID data in a timely mode for error correction. The proposed approach here guarantees to be a cost effective approach as only sparse Bluetooth nodes are employed and in addition usage of RFID is restricted to certain areas. Thus, the power consumption of the user′s handheld device could be reduced. The preciseness guaranteed in this approach is far better than other hybrid approaches [29],[17],[28],[40]. Moreover the system is capable of a routing service, which the Kleiner's approach [21] lacks. The introduced hybrid system offers a reliable solution which approach [29] fails to provide. The navigation scheme proposed in this thesis has optimal runtime compared to [56] and [53].

4 Efficient Localization and Navigation Methods

4.1 Introduction

A wide array of sensor technologies is available for competent indoor localization. The review weighs different factors on merits and demerits of these available technologies. The aim of this thesis is to explore and portray the most useful architecture and the best suited method that assures an effective indoor localization and unanimously functional across all location based service.

This chapter describes localization design based on Bluetooth, RFID, PDR and respective hybridization technologies. In section 4.2, Bluetooth localization based on multi-trilateration and Fingerprinting approach is presented alongside with roaming scheme employed for scalability and routing procedures. In section 4.3, RFID technology based indoor localization using RFID tag counts and their respective RSSI values are explored. The implication of the introduced RFID based localization is compared to that of available RFID based technologies (section 3.2). A Pedestrian Dead Reckoning system (PDR) employed using distance and direction estimate is described in section 4.4. There is a possibility of attaining an efficient localization when two or more based technologies are integrated. This termed as Hybrid system is explicitly described in section 4.5 and a possible Hybrid system is projected. The described Hybrid methodologies do fit well and are quite adaptive to accessible/non accessible wireless infrastructures. In section 4.6, an algorithm for an efficient navigation application with optimum run time is described.

4.2 Localization with Bluetooth

4.2.1 Methodology of Localization

Three key techniques for automated location estimation are triangulation, proximity and scene analysis (section 2.1.1). Location based systems can employ them either individually or in combination. The underlying idea across each of these techniques is described hereby.

A proximity based location sensing technique is based on the detection of an existing object or a user in its near proximity. The scene analysis sensing technique utilizes a captured scene from different viewpoints during calibration phase and utilizes the same to estimate the user's location. The triangulation, location-sensing technique applies the geometric characteristics of triangle to locate the existing position of the user. This is well achieved by measuring the distance of the user from diverse reference positions. In case of measurement of distance with lateration technique, three general approaches are employed.

- Direct measurement of distance utilizing a physical action or movement.
- Received signal strength method that makes use of signal intensity and power levels. The intensity of an emitted signal decreases as distance from source increases.
- Angle of Arrival (AOA) that considers the incoming signals to estimate the position of an object.

In this perspective, when radio wireless techniques are considered that utilizes Radio signal strength (RSS), this may prove far worth in terms of simplest means of tracking and locating users at indoors and remains inexpensive. The hitch of this approach is accuracy when building topology is subject to changes.

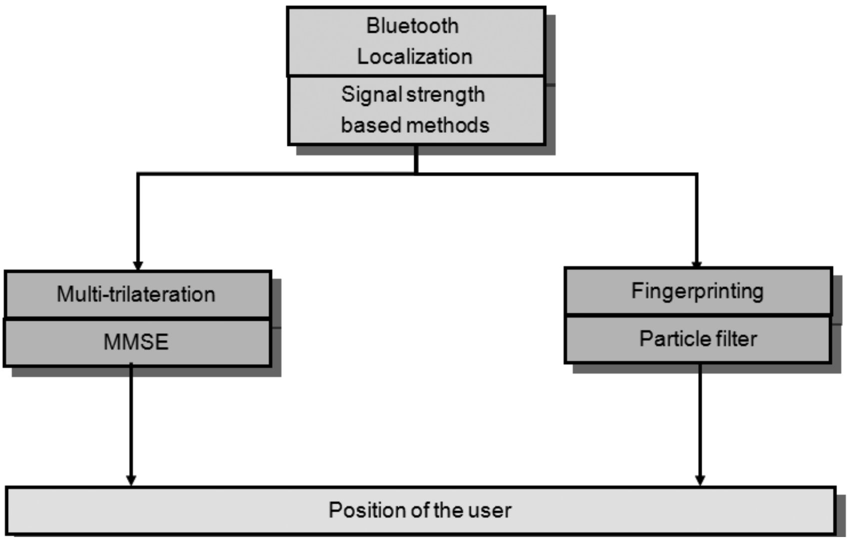

Abbildung 4.1: Methodology of localization using Bluetooth technology

The methodology applied for Bluetooth based indoor localization in this thesis is by employing trilateration and Fingerprinting. At first instance, imprecise measurements are corrected by a multi-trilateration approach to achieve the actual position of the user. Secondly, the particle filter based Bluetooth Fingerprinting approach is applied to estimate the position of the user. The methodology of localization is shown in the figure 4.1.

4.2.1.1 Multi-Trilateration Approach

The assumption for all RSSI based localization methods is that the signal strength decreases with increasing distance from the transmitter. In outdoors, where there is no reflection, the signal strength is inverse to the squared distance whereas at indoors the variation occurs due to multipath effects like reflection, noise and interference with other wireless technologies which operate in 2.4 GHZ frequency band.

Multi-trilateration is the method of estimating the actual position of the user from calculated distances between the transmitters and the received signal strengths. The distance between the reference nodes and the receiver can be estimated from the amount of signal attenuation along the propagation path and from the transmission power. By making out the distance between the receiver and the connected beacons, the actual location can be calculated.

In the proposed scenario Bluetooth reference nodes called Bluetooth beacons, which recognize their own position are installed in the environment. The Bluetooth beacon enters an inquiry scan state at regular intervals from the standby status. Once the mobile device invokes an inquiry, these Bluetooth beacons respond to the inquiry with FHS packet. The mobile device then enters the page state and gets connected to the encountered Bluetooth beacons. The mobile device is sending within each odd timing slot a signal to one of the beacons with transmission power $\mathbf{P_{tx}}$. On the other end the mobile device receives and measures the receiving power $\mathbf{P_{rx}}$. The distance estimates are then calculated using the log-normal path loss model which is the generalized Friss formula. The log-normal pass loss model admits that the received power varies when measured at different locations with the same distance between the transmitter and receiver. The Gaussian random variable becomes the log normal random variable when transformed into linear domain. The distance estimate is given by the equation 4.1.

$$P_{rx} = P_{tx} - 10\log(d_i) + \alpha \tag{4.1}$$

Which can be generalized to estimate the distance as in the equation 4.2.

$$P_{tx} - P_{rx} + \alpha = 10\log(d_i) \tag{4.2}$$

Where d_i denotes the RSSI-based distance estimate between the mobile device and beacon i and α is the path loss coefficient which is a metric for the attenuation of the signal along its propagation path from sender to receiver which is justified from prior measurement during the calibration phase. Typically the path loss coefficient varies between 1.5 and 5. The value of path loss coefficient measured is 2.09.

However, the transmitting power and receiving power cannot be measured directly. The Received Signal Strength Indicator of the Bluetooth beacons measures the absolute RSSI in dBm. The mobile device broadcast the packet requesting the Bluetooth beacons to transmit their own position and the absolute RSSI. The distances between the mobile device and the Bluetooth beacons are then calculated from the absolute RSSI obtained from the Bluetooth beacons by transforming the equation 4.2 to equation 4.3.

$$d_i = 10^{-r_i + \alpha} \tag{4.3}$$

Where d_i denotes the distance estimate between the mobile device and beacon i, r_i is the absolute RSSI obtained from beacon i and α is the constant obtained from the experimental measurements made during the calibration phase. Once the distance of the mobile device to the beacons is estimated, the position of the mobile device is calculated using the multi-trilateration method.

Minimum Mean Square Error (MMSE): Multi-trilateration can be derived from trilateration where the position of the unknown node from the set of intersection points is computed. The Minimum Mean Square Error (MMSE) is the algorithm opted for multi-trilateration. Since there is imprecise distance informations, it is very unlikely to find a single solution point that is the intercept of three or more distance estimates from beacons in 2D-Space.

The MMSE algorithm works as follows. The whole location space is divided into n grid points with a distance of 50cm each. The grid point which is the candidate for minimizing the distance error between the RSSI calculated distance and the estimated coordinate distance is opted as the actual position. For each grid point, the distance d_e between the grid point (x_e, y_e) to each of the beacons i is estimated as in the equation 4.4.

$$d_e = \sqrt{(x_i - x_e)^2 + (y_i - y_e)^2} \tag{4.4}$$

Where $i = 1...N$ beacons and (x_e, y_e) is the coordinate of the grid point and (x_i, y_i) is the coordinate of the beacon. The difference between the distance d_i calculated from the RSSI measurement and distance d_e is then computed. Δ_i expresses this difference in the equation 4.5.

$$\Delta_i = |d_i - d_e| \tag{4.5}$$

The overall error estimation function delta is given by 4.6.

$$\Delta = \sum_{i=1}^{N} \beta {\Delta_i}^2 \tag{4.6}$$

Where β is the assumed constant which is $\frac{1}{d_i}$ .The algorithm is repeated for n grid points and the candidate grid point (x_e, y_e) that minimizes Δ is the computed position of the user.

4.2.1.2 Particle Filter based Fingerprinting Approach

The Fingerprinting approach overcomes signal strength deviation by instructing the variation to the localization system. During the training phase, the varying signal strengths measured at different location points are modeled as a Fingerprint. Each of the employed location points has a varied signal strength. To localize the mobile user, the measured signal strength Fingerprints are compared with the Fingerprints recorded during the training phase. The location of the recorded Fingerprint that is more similar to the measured Fingerprint is believed to be the target location.

Setup phase: To model the Fingerprints, the Bluetooth beacons are placed at static points. The signal strength of the mobile device to these static beacons is measured by fixing the mobile device at a given location and measuring the signal for an hour. The mean of the signal strength at different locations is shown in the figure 4.2. Finally the Fingerprint is made out of the measurement. The Fingerprint F is tagged with the location and their corresponding RSSI value which is represented as $l_1, l_2...l_n$ and $r_1, r_2....r_n$ respectively. Here n denotes the number of locations. These Fingerprint values are utilized in the online phase to estimate the appropriate position of the user.

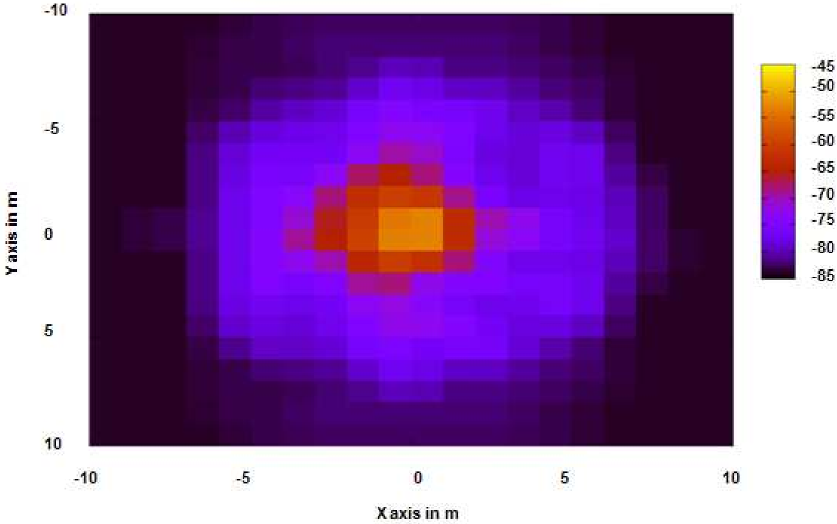

Abbildung 4.2: Bluetooth Fingerprints

Online phase: The deterministic approach for locating the user is to find the location from the Fingerprint which is the candidate for the smallest Euclidean distance in signal space. During the online phase, the signal strength of the mobile device is measured with respect to each of the Bluetooth beacons. This is represented as $R_1, R_2....R_n$. Then the estimation of the shortest signal distance between the measured RSSI and the RSSI from the Fingerprint (obtained during the setup phase) is done. The corresponding location of the RSSI, tagged in the Fingerprint that has the shortest signal distance to the measured RSSI is taken as the appropriate position of the user to the measured beacon. The appropriate position is expressed as (x_r, y_r) to each of the beacon r. The approximate position (x_r, y_r) computed from Bluetooth RSSI Fingerprinting is fused in the particle filter(section 2.1.2.1) to determine the position of the user. This is done by updating the weights $W_i(x_k)$ for each particle with respect to the Bluetooth beacon with the position information obtained from the Bluetooth Fingerprint.

$$W_i(x_k) = C * e^{(-\frac{(x_k - x_r)^2 + (y_k - y_r)^2}{2\sigma^2})} \tag{4.7}$$

Where $C = W_i(x_{k-1}) * \frac{1}{\sigma\sqrt{2\Pi}}$ and (x_k, y_k) are the position coordinates of the particle,(x_r, y_r) the position coordinates calculated from Bluetooth RSSI measures and σ is calculated from the prior measurement(section 5.2.1). The particles are then normalized and resampled.

4.2.2 Routing in Bluetooth

Routing is the process of selecting a path in a network along which to send network traffic. Routing of data is important for many location based services. For instance, when tracking peoples the localized information has to be routed to the server or aid in transferring data between as many as users within the same location.

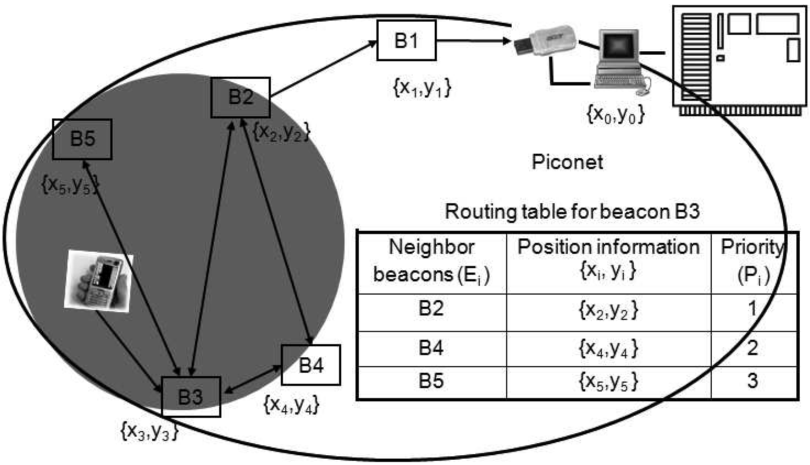

Abbildung 4.3: Routing in Bluetooth

Tiny screens and scare resources make the use of maps on mobile devices a challenging task. Therefore, a simplified presentation including maps that are relevant to the used regions is opted. The map of the particular region is generated from the server based on the request from the mobile. Static geographic routing routes service solely based on the position information of the Bluetooth beacons. Each beacon is informed with its own position. To do the path planning, the beacon identifies the neighbors and receives its position by paging with the neighbors. Each beacon build a table with the neighbor beacon Bluetooth address, Position information and the priority it gives to the neighbor beacon based on the shortest distance to itself.

Let n be the number of Bluetooth beacons in the system. Each Bluetooth beacon inquires and finds its neighbors ((B_i) where $i = 1, 2...n - 1$). Also the beacons obtains the position coordinates (X_i, Y_i) of neighbor beacons from the server. Based on this information it chooses the closest neighbor beacon (N_i). Once the closest neighbor is chosen, it assigns priority value (P_i) to each neighbor beacons. The choice of forwarding the service is based on the priority value of the beacons. When the mobile device requests map from one of its connected beacon, the beacon forwards the request to its closest neighbor which in turn forwards it to the server through its preferred neighbors. The map service from the server is then routed to the mobile device, through the established route. Unlike a dynamic routing, this results in significant reduction in routing overhead, which in turn saves much energy for other communications. The routing in Bluetooth is shown in figure 4.3.

4.2.3 Roaming in Bluetooth

The localization is done with the nodes in the piconet where a master can connect up to 7 slaves. When the network is scaled over a large building and with the user walking thorugh the network, the master node needs to get connected to the new slave nodes inorder to provide the localization service. For example, when a user walks around with his mobile device, he may lose the connection when he is not in the range of transmitting antenna. The mobile device has to be reconnected to the new beacons in the scatternet to localize itself. However, the mobile device has no knowledge about the nodes in the environment. The mobile device has to invoke an inquiry each time to find and get connected to the new beacons. However, the consumed inquiry time is much higher (maximum of 28s). The mobile device has to wait till it gets connect to the new beacons or there should be a way out to get connected to new nodes without interruption in service. A promising solution to the above problem is roaming. When the user moves from one zone to another, the connection and the service will be transferred in such a way that the user detects no interruption in service.

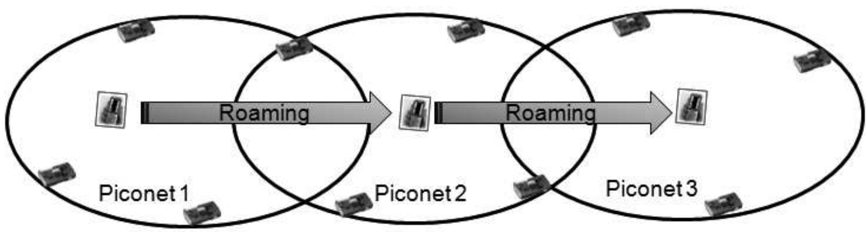

Abbildung 4.4: Roaming in Bluetooth

In the proposed system, each of the beacon nodes learns about its neighbor nodes. When the user with the mobile device which acts as master enters the piconet, it gets connected to the beacons which act as the slave nodes. When the user with the mobile devices is in motion and is leaving the piconet, it tries to get connected to the new beacons in the environment by receiving the information from the connected beacons.

In detail: when the mobile device moves through the environment, it will lose connection to the beacon that it has already paged. When the mobile device has less than four connections, it tries to connect to the neighboring beacons in its range through paging procedure. The mobile device receives the information about neighboring beacons from the beacons it has paged with. The mobile device tries to connect to the new beacons while performing the localization on the other hand. Since the mobile device receives the address from the closest connected beacons and establishes the connection to the neighbor beacons, it takes no separate time for connection establishment. This results in providing an uninterrupted service to the user. The roaming in Bluetooth is shown in figure 4.4. The pseudo code of the Routing and Roaming algorithm executed on the master device and the beacons is described below. Master node:

```
Start :
Invoke Inquiry ;
Connect to the beacons;
While connection==TRUE
  For each beacon
     Request RSSI;
  Execute localization ;
  If (no-of-connected-beacons < 4) //Roaming code for uninterrupted service
          Nearest-connected-beacon=beacon with least RSSI;
           Request BT-ADDR of neighbor-beacons from the Nearest-connected-beacon;
          Connect to the new beacons;
goto 3;
```

Connected slave beacon:

```
Start :
Invoke Inquiry ;    //Roaming code for uninterrupted service
Write BT_ADDR of neighboring beacon into EEProm;
Build the routing table ;
Listen for connection request
  Accept connection from master node;
  If (request for RSSI)
          Measure absolute RSSI;
          Send absolute RSSI;
  If (request for neighboring beacons)   //Roaming code for uninterrupted service
          Read BT_ADDR of the neighboring beacons from EEprom;
          Send BT_ADDR to the master;
```

```
goto 19;
```

4.3 Localization with RFID

Recent advances in RFID technology had opened new avenues for ample applications. Conceivably, RFID may be employed across different applications in the near future due to its compactness and cost efficiency. In recent years, RFID had been exploited to a great extent for self localization and navigation purposes. RFID dominates other wireless technologies when it comes to indoor localization as it pledges supremacy with its precise positioning ability. Today's indoor localization for pedestrians based on RFID technology has fascinated society in terms of economic and scientific scenario and is employed to a large extent in commercial areas such as healthcare, automotive and chemical industries for various purposes. Although RFID technology remains preeminent for robot localization, the size and weight of the long range reader antenna hampers its usage in pedestrian localization. Nevertheless, the compact short range RFID readers remain well suited for pedestrian localization.

The other vital attributes that RFID technology inherits are user-friendly, highly secure and cost efficient. There had been multiple localization methods based on RFID technology that localizes the user either using the signal strength of the tags or tag information (3.2). In these localization methods the tags are installed in an environment and RFID reader monitors these tags controlled by a person. In few other cases of RFID localization, the reader compares the different received signal strength measures of the active tags to estimate the distance between tag and the reader. On the other hand, some approaches utilize likelihood of tag detection to localize the user. In this section, the localization methods based on RFID technology is presented using tag detection count, the RSSI and a novel method with the combination of both tag detection count and RSSI.

4.3.1 Methodology of Localization

The infrastructure shown in figure 4.5 comprises of passive RFID tags for tracking the position of a user, a RFID reader to interrogate and retrieve the tag ID and the tag RSSI values and a mobile that acts as a graphical user interface for the user. Tags are positioned horizontally and vertically on the floor to gain detection irrespective of the orientation of the antenna. This is because, there won't be any detection of the tag if the reader is exactly perpendicular to the tags. Currently the reading range of short range UHF RFID readers is around 1.5m. As it should be worthwhile when implemented for a pedestrian purpose, the readings are obtained by placing the reader at waist level (assuming that the user should either carry them in trouser pockets or in hand bags). Each tag's location information is programmed in respective tag ID's. By issuing a single low level communication command, the RFID reader detects

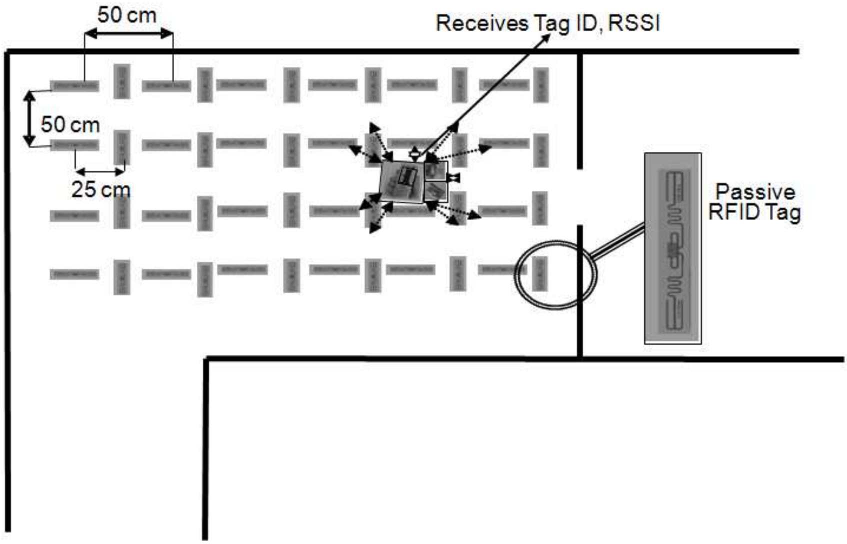

Abbildung 4.5: Localization with RFID

multiple transponders and this procedure is termed as inventory. As a result one gets a sequence of byte streams that contains a message ID, source name, inventoried tag IDs, respective timestamps and tag RSSI values, as well as the result code indicating success or failure for the inventory.

In brief: The mobile device invokes an inventory command to the RFID reader that in turn executes the inventory operation. The reader then confers back to the mobile with tag information and their respective tag RSSI values. The mobile device execute the inventory for a second and based on the received tag information received as a result from each inventory operation, the mobile device estimate the tag detection count. Tag detection count is nothing but the number of times the tag is detected when executing the inventory operation for a second. Additionally, the tag RSSI values are received as additional information along with the tag's information. By fusing tag RSSI measurements with tag detection count, a mobile user's location is tracked with high precision. The approaches that are used for RFID indoor localization in this thesis is tag detection count based localization, RSSI based localization and a combined approach. First, the localization of the user based on the posterior probability calculated from the prior probability and the likelihood function is enlightened. Secondly, the localization based on signal strength information is explained and finally the cohered approach based on the tag detection count and the RSSI is elucidated.

4.3.1.1 Localization based on Tag Detection Count

User localization by tag detection count has been widely described in literature. However, these approaches lack reliability due to false readings. The optimization of the approach is implemented in order to have the reliable localization. When receiving the inventory command from the mobile device, the RFID reader executes an inventory procedure to detect the passive RFID tags. The tag's 3D position coordinate (X, Y, Z) is integrated in the tag ID. Here the third dimension Z, stores information such as the floor number instead of height values. The inventory procedure is repeated until a second to estimate the tag detection count. A maximum 5 or 6 inventory can be possibly executed in a second. From the frequency of the tag being detected, the tag detection count is estimated.

The posterior probability of the tag detection is obtained from the probability of tag detection count and the likelihood function. The posterior probability is mapped to a sensor model to obtain the distance that is used to update the weights of the particles in the particle filter. First, an overview of the sensor model is presented and then the estimation of probability of likelihood is described.

Setup Phase - Sensor Model based on Tag Detection: In general, the tag detection depends on antenna orientation, power supply used by the reader and the object to which the tag is attached. The sensor model is designed by placing tags horizontally at 10cm apart with the reader placed at the position $(0, 0)$ at a height of 50cm from the ground. A continuous inventory operation is executed for an hour. The tag detection count is considered for every second interval from the tags IDs collected during the continuous inventory. The same detection rate is obtained for all antenna orientation, except for perpendicularity to the tag. Usage of maximum power supply consistently resulted in better detection (see section 5.3).

Sometimes the tags tend to show false positive or negative readings. If the reader is not able to detect the tag in its proximity, it is classified as false negative whereas if the reader read a tag inapt (not in range) then it is determined as a false positive. Sometimes the tags that are far apart or more closer to the reader may endure different or inconsistent tag detection values. To overcome the above problem, the likelihood that the tag can be detected along with the tag detection probability is accounted for.

The sensor model is designed taking into account the probability of detection rate of tags over a particular period of time given the location l of the tags. The sensor model is shown in figure 4.6. Likelihood of tag detection is estimated from the large number

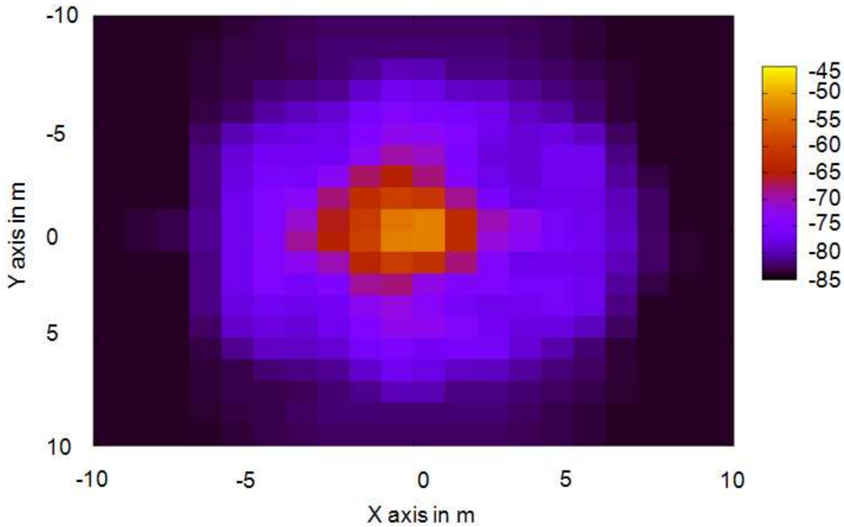

Abbildung 4.6: Sensor model based on tag count probability

of readings obtained during the continuous inventory operation. Likelihood of tag detection is defined as the probability that the detected tag be possibly at a given location. Once the probability of tag detection count and the likelihood is estimated, the posterior probability of tag detection is predicted. According to Bayes' Theorem in terms of likelihood, the posterior probability is directly proportional to the product of likelihood and prior probability. It is associated in this method as in equation 4.8.

$$P(T_i|z_{1t})\alpha L(T_i|z_t)P(T_i) \tag{4.8}$$

Here $P(T_i|z_{1t})$ is the posterior probability of detecting tag T at location l given the data's collected from $1....t$. $L(T_i|z_t)$ is the likelihood of detections T_i given the location l of the tag. Distance between tag and reader over time, prior probability, likelihood of tag detection and posterior probability are assigned to a lookup table and are used by the localization algorithm.

Online Phase: During the online phase, the inventory is carried out for a second and the probability of tag detection count $P(T_d)$ is inferred from the detected tags. These tag probabilities are then mapped to the lookup table to obtain the posterior probabilities of the corresponding tags. The corresponding distance of the maximum posterior probability is used as the tag distance value. The position of the user is estimated by allocating the tag location and distance values obtained from the lookup table to update the weights of the particles in the particle filter. The weights of the particles are updated using the equation 4.9.

$$W_i(x_k) = C * e^{(-\frac{(D(X_i)-D(T_i))^2}{2\sigma^2})} \tag{4.9}$$

Here $D(T_i)$ is the distance of the tag estimated from the sensor model based on the probability $P(T_i)$ and $D(X_i)$ is the distance of the particles to the tag which is estimated from the position coordinate of the tag and the particle. Whereas σ is obtained during the calibration phase(section 5.3.2).

4.3.1.2 Localization based on RSSI

There are two sorts of RSSI values namely the wideband and a narrow band available at the readers end. Wideband is a measure of the total signal level observed by the ADC(Analog to Digital Convertor) during its initial stage of receiving path. The narrowband RSSI value instead is derived after the digital filtering and encompasses information only on the signal level inside the channel bandwidth. However, Tag RSSI is the signal amplitude received during the inventory and is the only RSSI available to the end user. The tag RSSI is obtained as an additional information along with the Tag ID. In order to convert the value in dBm equation 4.10 has to be applied.

$$RSSI(dBm) = 0.8 * Tag_{RSSI} + Y + 24(dB) - AG \tag{4.10}$$

Here Tag_{RSSI} is the RSSI received during the inventory and AG is the antenna gain. The valid values are $0 = 24dB; 1 = 18dB; 3 = 12dB$. Y is the dBm measurement that would correspond to a narrow-band RSSI measurement of 0.The value of Y is calculated as in equation 4.11.

$$Y = -96 - 0.8 * RSSI_{threshold} \tag{4.11}$$

where $RSSI_{threshold}$ is 38 when it is configured in ETSI mode. The mobile device invokes an inventory operation requesting the reader to detect the tag and presents back the tag RSSI along with the location of the tags. The distances between the reader and the tags are then calculated from the tag RSSI obtained from the tags by using the modification of Friss formula as shown in equation 4.12.

$$d_i = 10^{-R_i+\alpha} \tag{4.12}$$

Where d_i denotes the distance estimate between the reader and tag i, R_i is the tag RSSI obtained from tag i, and α is the constant obtained from the experimental measurement made during the calibration phase. Once the distance of the reader to the tag is estimated, the position of the mobile device is calculated by feeding the distance calculated and the location of the tag to the particle filter. The weights of the particles are updated using the equation 4.13.

$$W_i(x_k) = C * e^{(-\frac{(D(X_i)-D(R_i))^2}{2\sigma^2})} \tag{4.13}$$

Here $D(R_i)$ is the distance of the tag estimated from the RSSI measurement and $D(X_i)$ is the distance of the particles to the tag which is estimated from the position coordinate of the tag and the particle. Whereas σ is obtained during the calibration phase(section 5.3.2).

4.3.1.3 Localization based on Cohered Tag Detection Count and RSSI

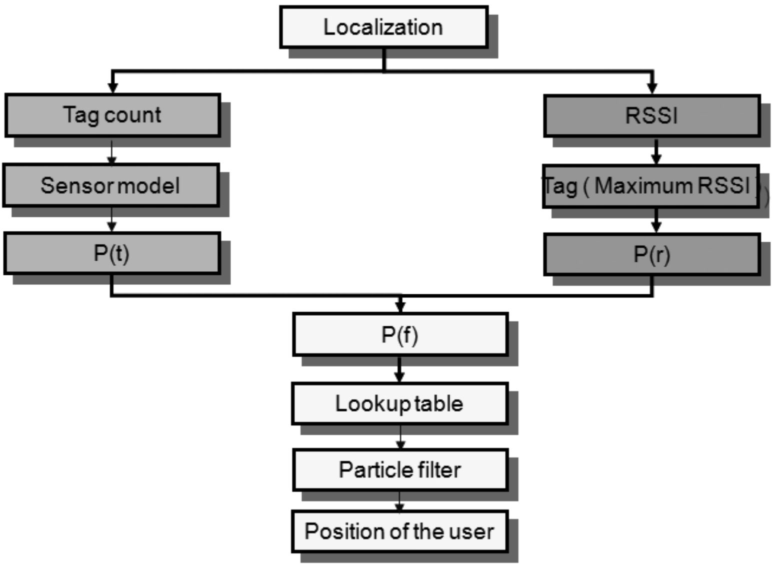

Abbildung 4.7: Methodology of localization using cohered RFID approach

Localization approach based on tag detection count and RSSI is explained in the section 4.3.1.1, 4.3.1.2 respectively. However, these approaches fail to be reliable, for the reason of false positive and false negative readings in case of both tag detection and RSSI. To overcome the same and to attain a reliable indoor localization using RFID, the fusion of tag detection and RSSI is done using a novel method. The methodology shown in figure 4.7 cohering tag detection count and the tag RSSI is carried out in three steps.

In the first step, the posterior probability $P(t)$ of tag detection count is estimated by mapping the received tag information to a sensor model. In the second step the probability of times the tag receives the maximum RSSI $P(r)$ is calculated. Finally, both probabilities are summed up and are mapped to a lookup table to estimate the final probability $P(f)$. This final probability $P(f)$ is then used to update the weights of the particles in the particle filter to estimate the position of the user.

Estimation of Probability of Tag Detection $P(t)$: The localization approach described above uses the tag detection count to estimate the distance between the reader r and tag t. The tag count decreases with increasing distance, however at times, probability of detection count of the tags will remain consistent or may provide false positive readings; therefore one cannot rely only on the tag count. This factor will lead to imprecise localization results. Therefore the position of the user is estimated not only by tag detection count but also the RSSI. The probability of tag detection $P(t)$ is obtained by mapping the tag count probability to the sensor model and estimating the posterior probability based on the likelihood function as explained in the 4.3.1.1.The maximum posterior probability is account as probability of tag detection $P(t)$.

Estimation of Probability of Tag's Maximum RSSI Count $P(r)$: When the tags are inventoried, the tag in proximity to the reader will attain maximum RSSI whereas the tags that are far enough will obtain lower RSSI. However, the tag RSSI may show up false positive or negative readings even though there is no disruption from the environment. In order to attain the reliability of the reading, the estimation of number of times that the tag has the maximum RSSI is performed and the probability inferred is $P(r)$. The conditional probability is made for a detected tag with maximum RSSI value given the detection rates as in the equation 4.14

$$P(r) = P(T_{maxrssi}|d_t) = \frac{P(d_t|T_{maxrssi})P(T_{maxrssi})}{P(d_t)} \tag{4.14}$$

Here $P(d_t|T_{maxrssi})$ is the detection probability of the tag provided the tag posses a maximum RSSI value.

Estimation of Probability $P(f)$: The false readings from both tag detection count and RSSI may reduce the accuracy level of the RFID system. In order to increase the accuracy and reliability, the probabilities obtained from the tag detection count and RSSI are fused together to obtain a final probability. The final probability is obtained by summing up probabilities $P(t)$ and $P(r)$ as in equation 4.15

$$P(f) = P(t) + P(r) \tag{4.15}$$

The final step in the localization algorithm is confining the users location by data's obtained from previous steps. The final probability values are mapped on a lookup table (designed during a calibration phase).The lookup model is shown in the 4.8.

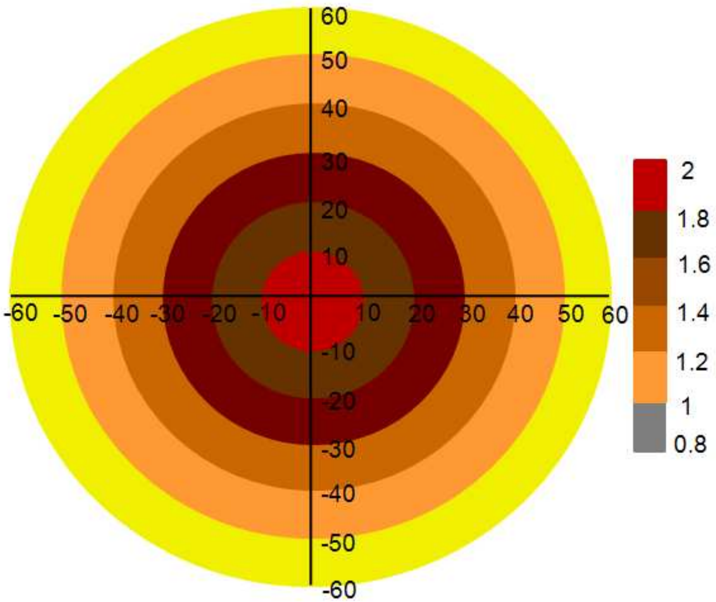

Abbildung 4.8: The lookup model of cohered RFID approach

The corresponding distances are obtained from the model by mapping the probability to the lookup table. The tags that have probabilities $P(f)$ less than 0.8 are ignored. This is because, these values contribute less to the final position estimation of the user. Finally the position of the user is estimated by allocating the tag location and distance values to update the weights of the particles in the particle filter. The weights of the particles are updated according to the equation 4.16.

$$W_i(x_k) = C * e^{(-\frac{(D(X_i)-D(F_i))^2}{2\sigma^2})} \tag{4.16}$$

Here $D(F_i)$ is the distance of the tag estimated from the sensor model based on the probability $P(f)$ and $D(X_i)$ is the distance of the particles to the tag. It is estimated from the position coordinate of the tag and the particle, whereas σ is obtained during the calibration phase(section 5.3.2).

4.4 Pedestrian Dead Reckoning System

In recent years Micro-Electro-Mechanical Systems (MEMS) sensors are gaining popularity as they are the best option for cost efficient indoor localization. The miniaturization, easy integration and cost efficiency make them attractive for users. The traditional Inertial Navigation Systems (INS) are employed in navigation and positioning of aircrafts and ships. They are highly sophisticated, sensitive and expensive devices and are mostly too large for a pedestrian navigation approach. However, with the growing market of MEMS sensors and falling prices, the proposed localization system took the advantage of small cost-efficient parts of an INS. Some indoor navigation services do not necessitate the preciseness rather require being inexpensive solution. In such cases MEMS sensors are the best option to implement. With the availability and affordability of MEMS sensors the platform is given for an Inertial Navigation System (INS) based approach.

Some work has been done so far using accelerometers to localize the user. An accelerometer measures the accelerating force acting on it. If those values are integrated once, the result will give the orientation of the acceleration (and over time the velocity) and a second integration results in the position. Given those values within an initialized inertial system one can define their position in relation to a known amount of time. An INS based on motion sensors is always inaccurate to some point and will become more inaccurate over time. To compensate this problem an INS is mostly used in a Hybrid setup combined with a GPS navigation system for example.

However, these approaches lack accuracy due to the accumulation of errors from the MEMS sensors and are computationally expensive. The simplest approach is to use the concept of step detection, where the steps made during the human gait is identified from the acceleration pattern. It is measuring the linear displacement of the user. The PDR system can detect steps in human gait and also calculate the direction of the detected steps. Based upon the detected steps and calculated direction, the system computes the user's location. This approach guarantees to be a cost efficient approach for indoor localization.

4.4.1 Methodology of Localization

Figure 4.9 depicts an overall schematic representation of a PDR system. The system employed consists of a MEMS module (which encompasses the accelerometer and the compass sensor) and a mobile that operates as a graphical user interface. The PDR system uses the accelerometer sensor to identify the steps from the human walking and the orientation estimated from the compass sensor. The acceleration follows a specific pattern during the human gait. The employed peak - declination algorithm finds the stride (two steps - being defined as a right foot step and a following left foot step) from the acceleration pattern. Form the stride detected, the distance the user walked is measured.

For a better stride detection, the user is supposed to carry the PDR system in his pocket or in the leg pouch. To estimate the orientation, the mean of the heading values during the stride made is measured from the compass sensor. From the displacement and the heading information, the position of the user is calculated. The particle filter in the mobile utilizes data from the MEMS module in addition to previous stored data history to compute the true position of the user.

The methodology of the PDR system is organized as follows. First, a procedure to measure the walking distance from the accelerometer sensor is explained. Secondly, computation of direction from the MEMS sensor is discussed. Finally, the estimation of position from the distance and direction values by feeding the appropriate position information into the particle filter is described.

4.4.1.1 The Distance Estimation

The most essential part in the PDR system is the distance estimation i.e., to measure the distance a person walks. The acceleration from the MEMS sensor follows a specific pattern depicting the steps during the human gait. However, the pattern differs depending on the walking style and footsteps. Hence the critical part of PDR system is the step detection. This is because the error accumulation in the PDR system is mainly due to false step detections. To detect accurate number of steps, thereby reducing the error in the PDR system, a novel peak - declination algorithm is employed for step detection. Once the steps are detected the distance is estimated from the number of steps made and the step size.

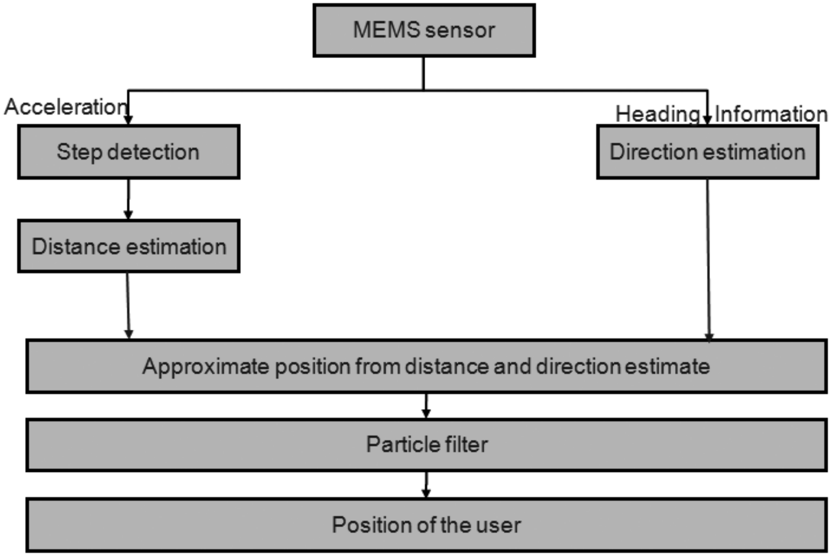

Abbildung 4.9: Methodology of localization using PDR

Step Detection: A popular approach in a PDR using an accelerometer sensor is the concept of step detection. This can be achieved by identifying a pattern within the raw data that can be declared as a step. Different approaches to this pattern recognition method are zero crossing or peak detection methods. Utilizing the zero crossing method, a step is detected, if the accelerometer's raw data values cross the zero line in a descending way (another possible version of this is to count all zero crossings and divide them by two). The peak detection methods try to identify the maximum peak within the raw data values and define those (most commonly positive) peaks as a step occurrence.

This approach obviously has its drawbacks due to the typical noise-affected accelerometer signal. They create many errors when the user moves in an unusual manner rather than his normal walking style. Therefore, smoothing filters have to be applied to the data before step estimation.

The peak - declination algorithm presented here diminishes sensor noise and is not susceptible to sensor drift occurring in other PDR systems. First, the pattern recognitions done from the raw acceleration values are explored. Then a novel step detection algorithm is explained followed by the distance estimation.

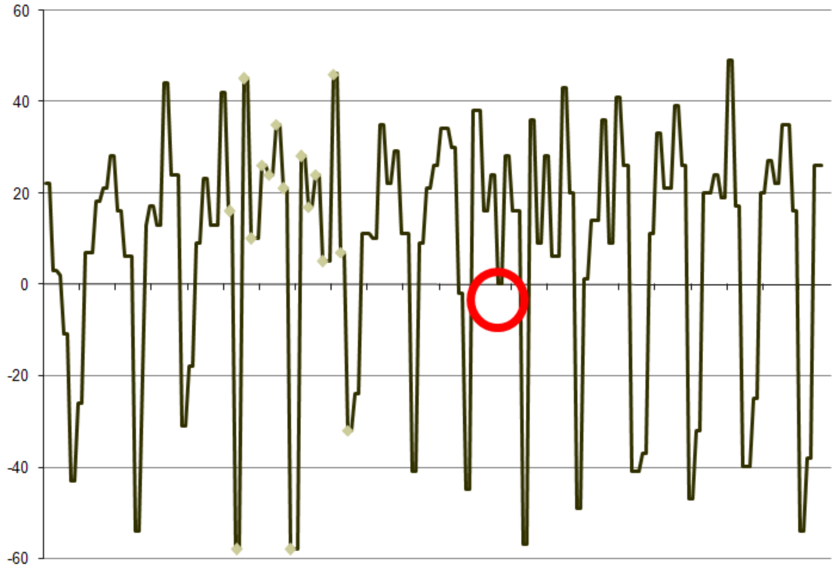

Abbildung 4.10: Recurring pattern of acceleration in PDR

The Pattern Recognition Algorithm: On examining the raw values delivered by the accelerometer, it revealed that the human gait resembles a specific recurrent pattern (Figure 4.10). By identifying the pattern within the raw data the number of steps of one such measurement can be detected and counted. However, minor flaws within this raw data showed that a simple zero-crossing algorithm is not sufficient for the step detection (marked by the red circle - Figure 4.10). By further analysis of the data it became evident that an easier, more forward way compared to single or double integration or frequency comparison could be used for a better step-detection.

The developed peak - declination algorithm overcomes the aforementioned problems. The peak - declination algorithm detects stride (two steps - being defined as a right foot step and a following left foot step) from the measurement. The measurement data is divided into four stages (Figure 4.11). The dotted lines show the different levels of the peak - declination algorithm: rest, negative peak, positive peak and following-declination. The recurrent pattern goes through four significant stages during a stride occurrence.

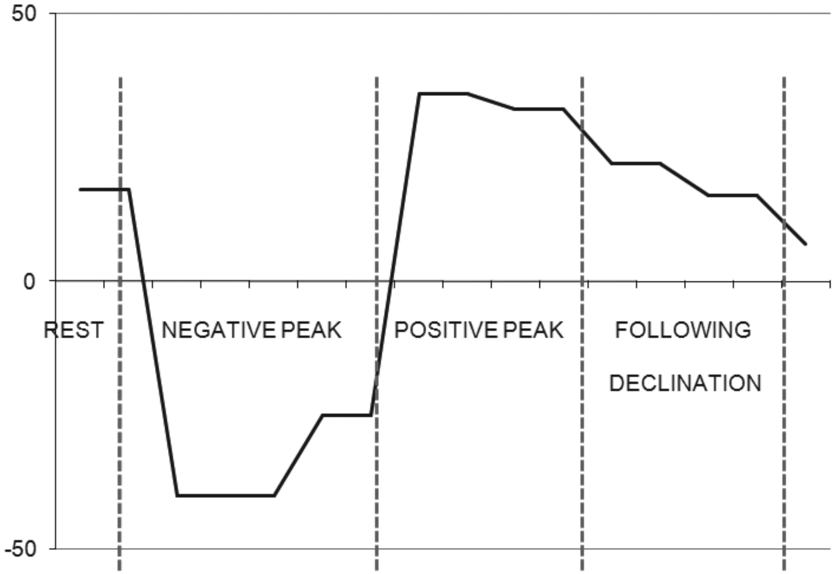

Abbildung 4.11: Stride occurance in PDR

Peak - Declination Algorithm: For the peak - declination algorithm, the vertical acceleration during human gait is not taken into account. The experiments led to the conclusion that information about horizontal acceleration is sufficient for a reliable robust stride-detection. The algorithm goes through four significant steps. The algorithm is initialized with the first set of raw values.

In the first step, the algorithm is looking for a level difference between the initial value and the successive received acceleration values. If a stride is made the acceleration values exceed the level difference and the algorithm executes the next step.

In the second step, the algorithm searches for the negative peak within the acceleration values.

In step three, the level difference between the negative peak and its successive acceleration values is searched. This level difference is based upon the significant pattern of the acceleration values of a stride and corresponds to the left foot movement of a stride occurrence. When this level difference is reached, the algorithm looks for the positive peak within a given set of successive values to overcome potential sensor noise or measurement errors and proceeds to step four.

Here the algorithm differentiates between a full stride occurrence (consisting of right and left foot movement) and half a stride occurrence (which can take place if only a right foot movement is committed or the user stopped or paused moving). Again this is based on a certain level. If the acceleration values fall below this level, the user is still moving and continues with the next stride. Therefore, a full stride occurrence has taken place. If the user stopped walking or made only half a stride occurrence, the successive acceleration values will stay at a level above the trigger for the next stride detection. The algorithm is as follows

```
Initialize initial_acceleration with acceleration ;
Measure acceleration ;
Initialize successive_acceleration with acceleration ;
If < initial_ accelaration − successive_ acceleration greater than level>
        Measure next 20 succesive_acceleration ;
         If <negative_peak from the successive_acceleration is TRUE>
                 If <negative_peak − succesive_acceleration greater than a level>
                         If <positive_peak from the successive_acceleration is TRUE>
                                 Full_stride ;
                         Else
                                 Half_stride ;
Else
        Measure acceleration ;
```

Finding the Correct Stride Length: The stride length of each human varies based on his walking style. The stride length cannot be estimated exactly based on the strides and the time information. However, the strides won't vary more than + or - 25cm. For the experiments a fixed stride length value of 2m similar to the work of Ladetto et al [24] is used. This stride length estimation proved to be correct in the experiments. But it can be easily adapted to the changing stride length by using additional external data when combining with other sensors. To calculate the distance d_a travelled, the number of strides and the stride length is took into account. The resulting walking distance made is given by equation 4.17.

$$d_a = \sum_{i=1}^{Noofstrides} stridelength \tag{4.17}$$

Where $Noofstrides$ is the actual number calculated by the peak - declination algorithm. However, the position of the user at each stride is estimated in order to improve the updating time. Hence, the distance d_a for each stride made is estimated as in equation 4.18

$$d_a = onestride * stridelength \tag{4.18}$$

4.4.1.2 The Direction Estimation

The other crucial component that affects the accuracy of the PDR system is the heading error. The heading value calculated for every stride is different from known direction of corridors. The ground truth value of direction of corridors is calculated during the calibration phase and the heading values of each stride are adjusted according to the ground truth.

To obtain the direction in which the human moves the orientation of a stride occurrence is estimated from the compass sensor. Mean direction value is calculated out of this array of heading values which are collected during the stride occurrences. The direction of the stride θ'_i is calculated with the arc tangent function atan2 with two parameters (x_i, y_i). Given the raw directions in degrees from 0 to 360, the radiant is calculated for every direction to determine the corresponding (x_i, y_i) values in relation to the unit circle. It is given by equation 4.19 and 4.20.

$$x_i = r * \cos\theta'_i \tag{4.19}$$

$$y_i = r * \sin\theta'_i \tag{4.20}$$

Where θ'_i is the averaged raw direction values collected during a stride and r=1 as the polar coordinates on the unit circle is took into account. The values x_i and y_i are summed up and used as parameters for the atan2 function as shown in the equation 4.21.

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \sum_{i=1}^{p} \begin{bmatrix} x_i \\ y_i \end{bmatrix} \tag{4.21}$$

Where p is the number of values taken into account for the detected stride. The result is the direction θ_a of the considered stride in the wider perspective of all occurring raw direction values during a stride. This result is then shrink back to the perspective of the overall direction of the stride calculating the values back from the radiant to degrees and a "$modulus360''$ operation. The result is the correct mean direction θ_a(Equation 4.22) of the stride.

$$\theta_a = \frac{atan2(x', y') * 180^\circ}{\pi} mod360 \tag{4.22}$$

4.4.1.3 The Position Estimation

The final step in the PDR system is the estimation of position coordinates from previous position coordinates, displacement made and the mean direction obtained for a single stride. The PDR system has to be initialized with the starting position and this is the main drawback of the system. However, when used in combination with other sensor technologies, the PDR system can initialize the starting position from the position calculated from the other sensor technology. Once the distance and direction is estimated for a stride, the cartesian coordinates of the new position are calculated with the previous position coordinate as the starting point. The Cartesian coordinates of the new position (x_a, y_a) at the time t=k is calculated as in equation 4.23.

$$\begin{bmatrix} x_a \\ y_a \end{bmatrix} = \begin{bmatrix} x_{a-1} + d_a * \frac{cos\theta_a * 180^\circ}{\pi} \\ y_{a-1} + d_a * \frac{sin\theta_a * 180^\circ}{\pi} \end{bmatrix} \tag{4.23}$$

Where (x_{a-1}, y_{a-1}) is the previous position coordinates and d_a is the displacement made with θ_a the mean direction value. This appropriate position is used to update the weights of the particles in the particle filter as in equation 4.24.

$$W_i(x_k) = C * e^{(-\frac{(x_k - x_a)^2 + (y_k - y_a)^2}{2\sigma^2})} \tag{4.24}$$

Where $C = W_i(x_{k-1}) * \frac{1}{\sigma\sqrt{2\Pi}}$ and (x_k, y_k) are the position coordinates of the particle, (x_a, y_a) is the position coordinates calculated from the MEMS sensor, whereas σ is obtained during the calibration phase(section 5.4.2.1). The particles are normalized and resampled.

4.5 Hybrid Systems

All sensor technologies adapted for indoor localization of pedestrians have their own merits and drawbacks. For instance, Bluetooth has a fulfilling level of accuracy, reliability and remains cost efficient, however, it fails to provide an uninterrupted service when scaled.

In much of the scenarios, the precision remains a major obstacle. Although, RFID could overcome this obstacle, it lacks flexibility and routing capability when it comes to localization. With the usage of a PDR, a standalone energy efficient system is feasible but the downside is that it accumulates errors with increasing distance and needs to be initialized with a starting position.

High precision sensors like UWB lack flexibility and are expensive. In addition, some of the sensors are not integrated in today's hand held devices such as smart phones. In order to find a compromise between costs, accuracy and to have a single solution for indoor localization that could satisfy all the criteria for localization, sensor hybridization remains a valid approach. In this section, the different combinations of hybridization of sensor are discussed. First the combination of Bluetooth and PDR is explained followed by the hybridization of RFID and PDR. Finally, the fusion of the three sensor technologies taking the advantage of the sensors in an efficient manner is explained.

4.5.1 Hybridization of Bluetooth and PDR

4.5.1.1 Methodology of Hybrid BT - PDR (Hybrid BT - PDR)

Scalability is the ability to sustain performance regardless of expansion of the network. Affording an uninterrupted service when scaled is one of the problems with today's Bluetooth based positioning. The pivotal reason for the above is that Bluetooth, being a short range wireless technology, can offer its service for up to few meters. The user should stay linked with Bluetooth beacons without interrupted connection.

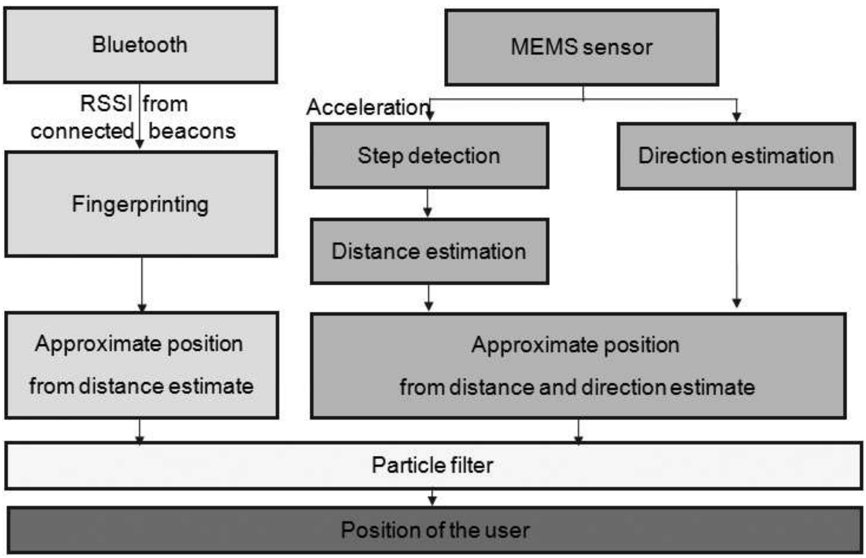

Abbildung 4.12: Methodology of localization using Hybrid BT - PDR

When interruption occurs, the user has to connect to new beacons leading to ample time consumption in providing the service as it has to be paged for every connection. The Bluetooth roaming scheme as in section 4.2 is employed. Sometimes the time taken for paging will rise to interrupted service for few seconds. To overcome this and to provide an uninterrupted service the Bluetooth is combined with low cost MEMS sensors. Whenever there is a failure in connection with Bluetooth beacons, the MEMS sensor provides an add-on support to Bluetooth beacons thus increasing the scalability of Bluetooth.

The system employs Bluetooth beacons (acts as access points), a MEMS sensor (detects users position from acceleration and orientation values) and a smart phone that operates as a graphical user interface. The density of the Bluetooth beacons is reduced.

Figure 4.12 depicts an overall schematic representation of Hybrid BT-PDR solution. In brief; approximate position of the user is estimated from the distance obtained from the RSSI measures of different Bluetooth beacons using the Bluetooth Fingerprinting approach (section 4.2.1.2) and approximate location information of the user is predicted using the MEMS sensor measures (section 4.4.1). Both these approximate position information's are fused together in the particle filter. The particle filter in the mobile utilizes data from the Bluetooth beacons and the MEMS sensor module in addition to previous stored data history to compute the true position of the user.

Due to its influence over accuracy, in addition to its rapid calculation, the Bluetooth RSSI Fingerprinting approach remains exceptional than multi-trilateration. In addition, the appropriate position of the user is obtained from the MEMS sensor as explained in section 4.4 using the acceleration and direction measurement values. The starting point of the PDR system is initialized from the results of Bluetooth Fingerprinting approach. In the Hybrid BT-PDR both the appropriate position of the user obtained from the Bluetooth Fingerprinting approach and PDR approach are fused together in the particle filter to estimate the position of the user. However at times, when the user moves from one zone to another, the Bluetooth has to establish connections to the new beacons for localization. In such cases, the localization service is provided to the user uninterrupted by using only the PDR system. The weights of the particles in the particle filters are updated in either case, when the Bluetooth RSSI measure exist or when it doesn't exist as shown in the equation 4.25 and 4.26. If Bluetooth measure exist

$$W_i(x_k) = C * e^{\left(-\frac{(x_k - \frac{(x_r + x_a)}{2}^2) + (y_k - \frac{(y_r + y_a)}{2}^2)}{2\sigma^2}\right)} \tag{4.25}$$

If Bluetooth measure doesn't exist

$$W_i(x_k) = C * e^{(-\frac{(x_k - x_a)^2 + (y_k - y_a)^2}{2\sigma^2})} \tag{4.26}$$

Where $C = W_i(x_{k-1}) * \frac{1}{\sigma\sqrt{2\Pi}}$ and (x_k, y_k) are the position coordinates of the particle ,(x_r, y_r) are the position coordinates calculated from the Bluetooth RSSI measurement and (x_a, y_a) are the position coordinates calculated from MEMS sensor.σ is obtained by averaging the σ from Bluetooth Fingerprinting approach(section 5.2.1) and σ from PDR (section 5.4.2.1)

4.5.1.2 Advantages and Drawbacks of Hybrid BT-PDR

The Hybrid BT - PDR systems takes advantage of the both sensor technologies. The PDR system employed aid the Hybrid BT-PDR system in providing uninterrupted service, when there is no information from Bluetooth. On the other hand, the Bluetooth system helps to initialize the PDR system with the starting position. The Hybrid BT - PDR system is able to route information with the Bluetooth technology. Moreover both technologies are readily available in mobile phones, thus could be implemented in smart phones without additional hardware. Since the density of the Bluetooth beacons is reduced it proves to be cost efficient than Bluetooth based localization. The Hybrid BT-PDR system is not very precise compared to the RFID technology. However, it is well suited for the applications where the coarse grained localization is enough.

4.5.2 Hybridization of RFID and PDR

4.5.2.1 Methodology of Hybrid RFID - PDR (Hybrid RFID - PDR)

Flexibility is the ability of a system to adjust to changing or new environments. A flexible system can be easily reconfigured or adapted to location responses and system requirements. However, some localization systems are not flexible enough to be easily adapted to changing environments. In case of floor based RFID localization, it is not flexible enough to install the tags in the environment.

Because of its short reading range of the reader, the tags have to be placed at centimeters distance. This takes much human effort to install these tags. Moreover when it has to be replaced in some other environment either the tag has to be reprogrammed or the database that is previously built has to be changed. This involves much effort to reprogram the indefinite number of tags for a new location. Though some companies sell smart carpets with built-in RFID tags for efficient and economic utilization which could be flexible and time controlled approach, it is not readily available in the market and is incorporated as a choice.

RFID technology remains an efficient approach in terms of preciseness in localization. However, it fails when it comes to flexibility. In order to be much precise and flexible, the layout of tags is reduced and is confined. Nevertheless, to provide localization service across larger areas, the MEMS sensor is employed. As in the case of Hybrid BT-PDR, the Hybrid RFID - PDR also takes the advantages of precisenness from RFID system and cost efficiency of MEMS sensor, thus this combination remains efficient. The user is localized with the PDR system with the starting point incurred from the RFID system. Based on the result from the PDR system, the RFID system does the error correction after certain time interval. The resulting position is used as the starting point for PDR system. This will reduce the error accumulation in the PDR system. Moreover the power consumption and reduced density of RFID tags in the RFID system makes the Hybrid RFID-PDR to be an efficient and flexible system.

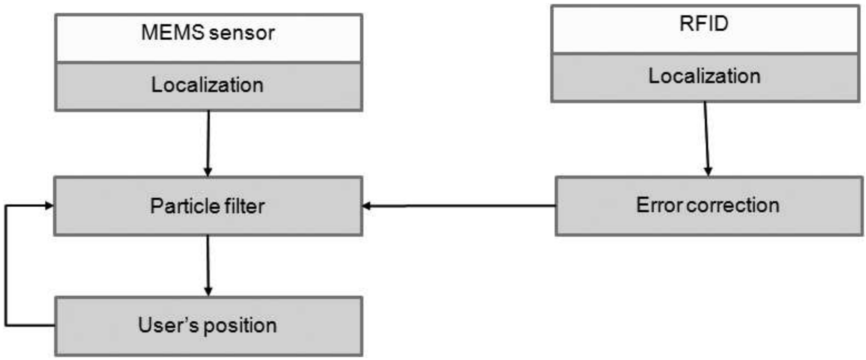

Abbildung 4.13: Methodology of localization using Hybrid RFID - PDR

The system employs a MEMS sensor (detects users position from acceleration and orientation values), RFID system and a mobile that operates as a graphical user interface. The RFID tags are laid at certain places at a distance interval. Figure 4.13 depicts an overall schematic representation of Hybrid RFID-PDR.

In brief; approximate position of the user is estimated with the PDR approach as explained in section 4.4. Based on the displacement result from the PDR approach, the RFID system is invoked. At regular intervals the localization is obtained from the coupled tag count and RSSI approach of RFID system as explained in section 4.3.1.3. This localized result is then used for the error correction in the PDR approach. This RFID localized position is then used as a starting point for the PDR approach. The particle filter in the mobile utilizes data from the MEMS sensor in addition to previous stored data history to compute the true position of the user. Updating the weights of the particles in the particle filter is according to the equation 4.27.

$$W_i(x_k) = C * e^{(-\frac{(x_k - x_a)^2 + (y_k - y_a)^2}{2\sigma^2})} \tag{4.27}$$

Where $C = W_i(x_{k-1}) * \frac{1}{\sigma\sqrt{2\Pi}}$ and (x_k, y_k) are the position coordinates of the particle ,(x_a, y_a) are the position coordinates calculated from the PDR approach. Here

$$\begin{bmatrix} x_a \\ y_a \end{bmatrix} = \begin{bmatrix} x_{a-1} + d_a * \frac{cos\theta_a * 180°}{\pi} \\ y_{a-1} + d_a * \frac{sin\theta_a * 180°}{\pi} \end{bmatrix} \tag{4.28}$$

where (x_{a-1}, y_{a-1}) is the previous position coordinates and (d_a) is the displacement made with θ_a the mean direction value. However, based on the displacement result from the PDR system, the RFID system is invoked. If the RFID result exist, the weights of the particles are updated as shown in equation 4.29.

$$W_i(x_k) = C * e^{(-\frac{(D(X_i) - D(F_i))^2}{2\sigma^2})} \tag{4.29}$$

Here $D(F_i)$ is the distance of the tag estimated from the sensor model based on the probability $P(f)$ and $D(X_i)$ is the distance of the particles to the tag. It is estimated from the position coordinate of the tag and the particle, whereas σ is obtained by averaging the σ from cohered RFID approach(section 5.3.2) and σ from PDR (section 5.4.2.1) . The resulting position (x, y) from the particle filter is used as the starting position of the PDR system as shown in the equation 4.30.

$$x_{a-1} = x \tag{4.30}$$

$$y_{a-1} = y \tag{4.31}$$

4.5.2.2 Advantages and Drawbacks of Hybrid RFID-PDR

The Hybrid RFID - PDR systems utilizes the advantage of both RFID and MEMS sensor technologies. The PDR system employed enables the Hybrid RFID-PDR system to provide the service to the user all the time. Additionally, the RFID system helps in initializing the PDR system with the starting position and also does the error correction at regular intervals.

The main advantage of the Hybrid RFID - PDR system is that it is very precise compared. Moreover it is flexible and cost efficient because of the reduced density of the tags. The drawback of the Hybrid RFID - PDR system is that it not able to route information without additional technology. However, the system can be combined with WLAN or Bluetooth enabling it to route information. Moreover the RFID technology is not available in today's smart phone.

4.5.3 Hybridization of Bluetooth, RFID and PDR

4.5.3.1 Methodology of Hybrid BT - RFID - PDR (Hybrid BT - RFID - PDR)

Hybridization of Bluetooth, RFID and PDR is designed considering advantages of the Bluetooth, PDR and RFID technologies. It is more complex to design a system that could be used for all type of application. On the other hand the number of sensor nodes might be huge, and also the overall costs of sophisticated hardware devices are pretty high, that many applications cannot afford. Therefore, the utility of exact localization algorithms is limited to some applications. To overcome this, the Hybridization of Bluetooth, RFID and PDR are proposed by reducing the density of the sensors needed.

The proposed Hybrid BT- RFID - PDR system satisfies the important criteria's for localization based applications. PDR can be used as a standalone system for localization, but it lacks to be precise which could be corrected by the RFID system. But some application requires routing of information. In such cases Bluetooth serves the purpose.

The combination of Bluetooth, RFID and PDR in an efficient manner satisfies the criteria's for localization and proves to be cost efficient and could be easily adapted for all type of localization applications. The resulting system consists of three software modules Bluetooth, PDR and RFID. These three software modules are executed on a smart phone. The Bluetooth enabled Smartphone is equipped with a RFID reader and a MEMS sensor. The Bluetooth beacons are installed on the floor whereas the RFID tags are laid over the floor at certain distance intervals. This reduces the density of the installed sensors used in the single sensor based solutions. Stationary Bluetooth beacons and RFID tags (transponders) in the pedestrian path serve as uniquely identifiable landmarks with known positions. Figure 4.14 depicts an overall schematic

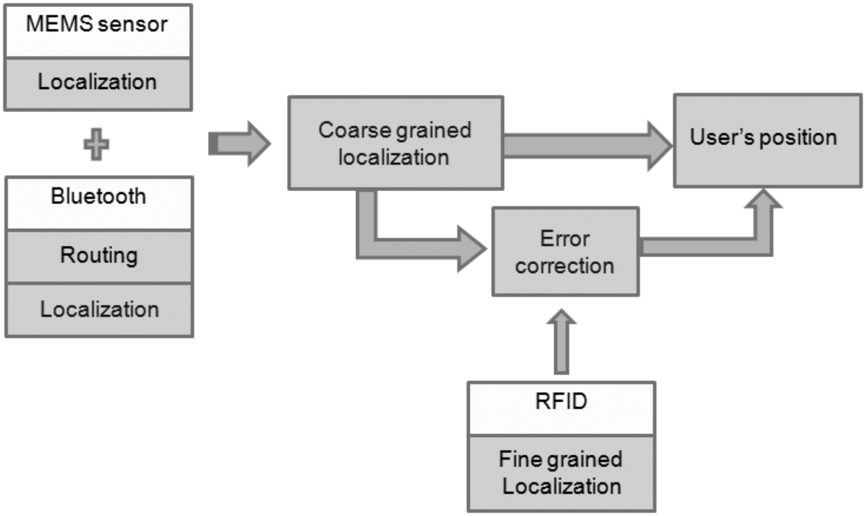

Abbildung 4.14: Methodology of localization using Hybrid BT -RFID- PDR

representation of the Hybrid BT-RFID-PDR. The basic principle of the Hybrid BT-RFID-PDR system is to locate the user coarse grained by using the signal strength information from Bluetooth and the position estimation from the MEMS sensor. At regular points precise RFID localization is executed to correct the deviated position.

Coarse Grained Localization: Many applications can tolerate position errors of some moderate degree of up to about 15%. For them, approximate localization algorithms might be interesting alternatives, due to their considerably lower hardware requirements in terms of radio modules, processor speed, and memory size, and so forth. The ultimate goal of (probably all) localization algorithms is to yield a very high precision at minimal energy costs. The coarse grained localization is obtained with Bluetooth and PDR system. The coarse grained localization of user is achieved with the same methodology of Hybrid BT-PDR as explained in the section 4.5.1.

Error Correction with RFID: The error rate may get worse either due to lower connection rate to the Bluetooth beacons and also due to the error accumulation from PDR system. To raise the preciseness of localization, the approach performs an error correction at certain areas using RFID based localization as depicted in section 4.5.2. Based on the displacement information from the PDR system, the Hybrid BT-RFID-

PDR system invokes the RFID localization. Thus the error correction is done at regular intervals with RFID system. The hybrid BT-RFID-PDR algorithm is depicted as follows.

```
While < to be localized >
 Initialize PDR system with Bluetooth_result_position ;
Execute coarse grained localization with Bluetooth and PDR;
If < displacement measured in PDR is greater than 10 m>
        Execute RFID based fine grained localization ;
         Initialize PDR system with RFID_result_position ;
End while:
```

4.5.3.2 Advantages and Drawbacks of Hybrid BT-RFID- PDR

The Hybrid BT- RFID - PDR systems takes the advantage from Bluetooth, RFID and MEMS sensor technologies. The PDR system employed helps the Hybrid BT-RFID-PDR system to provide the service to the user at any circumstance. On the other hand the Hybrid BT- RFID-PDR system helps in initializing the starting position of the PDR system with the precise RFID localization result. The main advantage of the Hybrid BT- RFID - PDR system is that it is very precise and it goes well for all applications. Moreover it is flexible and cost efficient because of the reduced density of the sensors. Moreover the system is able to route information. Though the RFID technology is not available in todays smart phone it is very likely to be in future's smart phone.

4.6 Indoor Navigation

The final definite purpose is to build a hand-held navigation system that could guide people at indoors similar to outdoor navigation that is currently available in the market. In the current epoch, indoor navigation services are gaining much attention as outdoor navigation and there has been an increasing necessity for directed guidance such as tracing a product in a shopping mall, locating a room of a patient or a doctor in a multi storey hospital, tracking a book in a vast library and many more. Generally path planning is done with A* and Dijkstra shortest path algorithms [59]. Some algorithms consider the semantic ontology of the building to satisfy the user's preference. However, optimizing the system's runtime remains an important factor for an efficient navigation algorithm. In this section, a navigation algorithm is presented considering the semantic ontology of the building infrastructure and optimized runtime of the system.

4.6.1 Methodology for Indoor Navigation

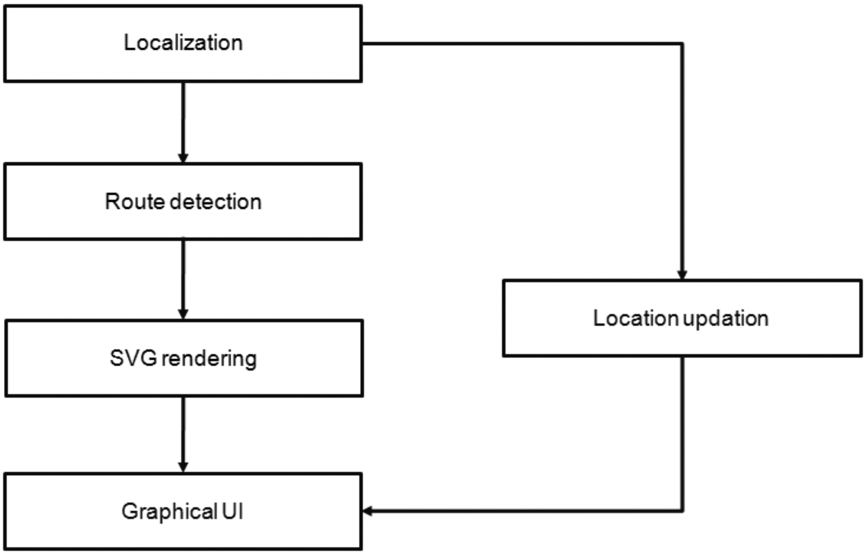

Abbildung 4.15: Methodology of navigation

The navigation system is divided into four modules: localization, route detection, SVG rendering and route update function [Figure 4.15]. The localization can be done with any one of the localization approach as explained in previous sections 4.2,4.3,4.4. Route detection is achieved by means of boundary Dijkstra that utilizes position estimates from localization approach. Once the route is detected, the user can visualize them through SVG rendering. Further the user's location is updated over the rendered route that facilitates the user in precise guidance.

4.6.1.1 Localization

The basic information needed for the navigation system is the current localization of the user. Although this can be manually incorporated to the system, it remains appropriate if the user is localized automatically. GPS works well in outdoors, but in indoors the localization can be done using sensor technologies. In the proposed navigation system, the localization is done with any one of the proposed technologies as described in section 4.2,4.3,4.4. The output of the localization is the 3D coordinate (X, Y, Z) of the person. It is more complex to adapt the system with the global coordinates (Latitude and Longitude). Therefore it is adapted to localize the user with the 3d coordinates with the origin $(0, 0, 0)$ at the left end of the building. Since the localization is done for an indoor area composed of the floors, the third coordinate Z indicates the floor number where the user is localized instead of the height information. Whereas if the person is in between 2 floors for instance in stairs, the Z coordinate will obtain the value of both floor.

4.6.1.2 Route Detection

Once the person is localized, the input i.e. the 3D position coordinate (X, Y, Z) is provided to the route planning algorithm to perform route detection. The proposed route planning algorithm is based on semantic ontology of the building infrastructure. Each building model encompasses rooms, stairs, floors, passage, and elevators.

This sort of modeling enables the algorithm to satisfy the reasoning of the user optimally. The semantic ontology is presented as a graph structure that maps the route

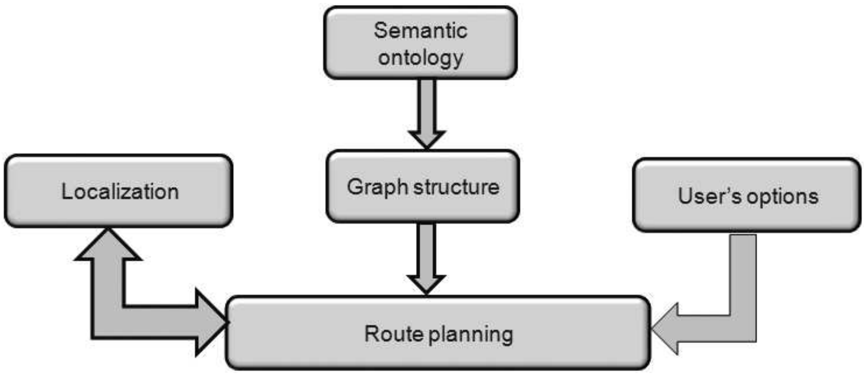

Abbildung 4.16: Route detection

considering current location and the user's preference. The route detection module considers the localized information and preference of the user, whereas the semantic ontology of the building to plan the route to the destination. The architecture of the route detection module is depicted in figure 4.16. The entire building is subdivided into passage elements. Each passage element composes elements rooms. These room elements are modeled as normal nodes. The border that connects the two passages modeled as the boundary nodes, whereas the stairs are modeled as special boundary nodes. The passages in each floor are numbered. Both the normal nodes and the boundary nodes carry additional information such as floor number and also passage number. Since the boundary nodes connect 2 passages it acquires numbers of both the passages. The normal nodes are well connected to boundary nodes. Each node contributes to a list of attributes such as (x, y, n, fn, pn).

```
Node(x,y,n,fn,pn)
          x:  X coordinate
          y:  Y coordinate
          n:  Normal node / boundary node / stair -boundary
                node / Elevator -boundary node
          fn  : Floor number
          pn :  passage number
```

The algorithm works with the boundary nodes from all possible floors including special boundary nodes such as from staircase, and elevator. Based on user's preference, the periphery of certain special boundary nodes can be removed before feeding the same to Dijkstra.

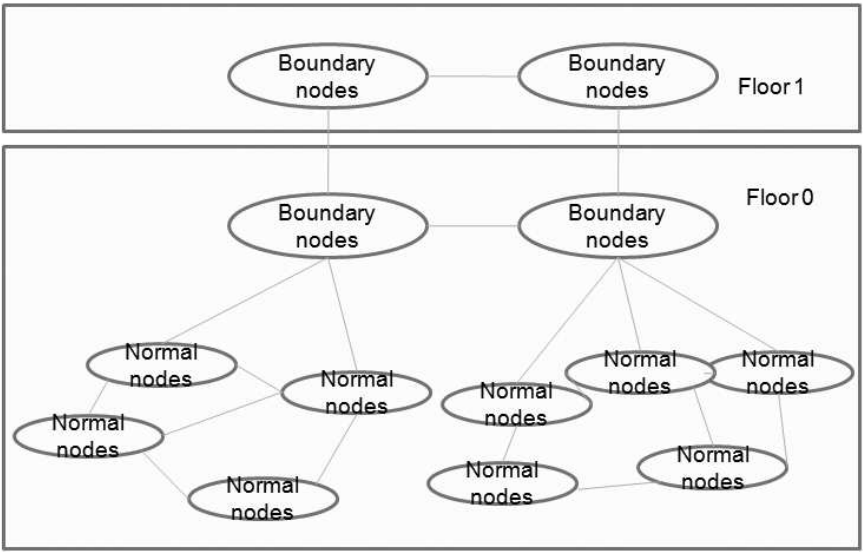

Abbildung 4.17: Graph structure

The figure 4.17 depicts the semantic ontology to a graph structure. The algorithm considers the current position (x, y, z) obtained from the localization, the destination position (x, y, z), graph structure and the user's preference as inputs. The algorithm is computed in four steps.

In step one, the start node at the proximity position of the user and end node proximity to the final destination are chosen from the set of assigned normal nodes. If the passage number of the start node and the end node are same then the route is planned with the normal nodes by connection the start node and end node. On the other hand, if passage number differs, it proceeds to the step 2.

In step 2, boundary nodes in closer proximity to start and end node is designated by comparing their node attributes. These boundary nodes contribute as a start and end node to the Dijkstra.

In step 3, the shortest path route is calculated using Dijkstra considering the user's preference and the node attributes. Dijkstra facilitate in calculating the shortest path as it is explicitly designed for a continuous and oriented graph profiles.

In step four, shortest route that had been calculated are embedded with the closest start and end node respectively. The algorithm is depicted as follows.

```
Function Path planning ( Current_position (x, y, z), end_position (x, y, z), options )
    sn(x, y, z, a, b):=nearest_node ( current_position )
    en(x, y, z, a, b):=nearest_node ( end_position )
    bsn(x, y, z, a, b):= nearest_boundary_startnode (sn)
    ben(x, y, z, a ,b):=nearest_boundary_endnode (en)
If ( current_position (z) =end_position (z)) then
    If ( Intraboundary ) then
            final_path := current_position U end_position
    else
            final_path := current_position U Intrafloor (sn, en) U
                             end_position
else if ( option= stairs ) then
            Elevator_edges := null ;
            intermediate_path :=sn U Shortest_path (bsn, ben) U
                                             Intraboundary (ben, en)
            final_path : = current_position U intermediate_path U
                             end_position
else if ( option=Elevator ) then
            Stair_edges := null ;
            intermediate_path :=sn U Shortest_path (ben, ben) U
                                         Intraboundary (ben, en)
            final_path := current_position U intermediate_path U
                             end_position
else if ( option=Shortest path ) then
           intermediate_path := Shortest_path (sn, en)
           final_path := current_position U intermediate_path U
                          end_position
return final_path
Function Shortest_path ( start_node , end_node)
Check Shortestpath
Path:= Dijkstra ( start_node ,end_node)
return Path
```

4.6.1.3 SVG Rendering

Once the route path is premeditated, it is subsequently visualized through scalable vector graphics, a language for describing two-dimensional graphics and graphical applications. SVG is a language for describing two-dimensional graphics and graphical applications in XML. SVG Tiny 1.2 is a W3C Recommendation, and targets mobile devices. Multimedia features such as synchronized interactive audio, video, and animation allow authors to create compelling content across platforms and devices, using open standards. The ability to render graphics on the fly lends itself naturally to using it for representing data such as graphs. The SVG map of the three floor building is stored prior in the mobile phone. The route is rendered online over the SVG map of the building by providing the (x, y, z) coordinates of the nodes to the rendering module. The coordinates of the nodes from the route planned is mapped to the corresponding coordinates in the SVG database. The route is rendered by connecting the SVG coordinates in order thus forming the route.

4.6.1.4 Route Updation

The location of the user is computed and updated constantly. The updated user's location is consistently checked and if it is within a distance of 1.5m from the directed path, the user is supposed that he stays in the path. Because the worst case error from the localized position would be + or - 1.5.In case the user strays from his directed path more than 1.5 m; the user will be alerted with the message that he is away from the path. Moreover it is also visualized the path the user is moving along with the route planned.

5 Experimental setup and results

Experiments are conducted to analyze the accuracy level and other localization criteria with the above mentioned systems. These experiments are performed by human users at indoors in a building belonging to Wilhelm-Schickard-Institute for Computer Science in Tuebingen, Germany. In this chapter, the hardware setup used for the experiments is briefly described followed by the localization results. The accuracy and reliability percentage based on each of the mentioned technologies and its hybridization is portrayed. Then a comparison of all the localization systems based on the criteria for localization is detailed to provide the conclusion about the best opted system for localization

5.1 Hardware Setup

The reason that the localization system should be compact enough for pedestrians has a great impact on the hardware design. Unfortunately, most of the best available platforms are made with heavy sensors with the user required to carry on his/her bag what makes it uncomfortable for the users. And none of the platforms is commercially available for autonomy support of the user. Moreover, because of the increase of computation, the GUI interface available for the users cannot be too compact.

On the other hand, the available sensors for localization require a special way of mounting, for instance the head mounted navigation system [38]. In order to resolve all these weaknesses, a compact hardware setup is designed for the experiments. The hardware setup [Figure 5.1] consist of the

1. BTnode [1] as Bluetooth setup
2. CEAN A528 UHF RFID reader [2] and Aliens Higgs RFID tags [6] as RFID setup
3. Honeywell 3D compass [4] as PDR setup and
4. Nokia Smart phone as user interface and Bluetooth master device

The hardware setup is designed with light weighted compact sensor and is put in

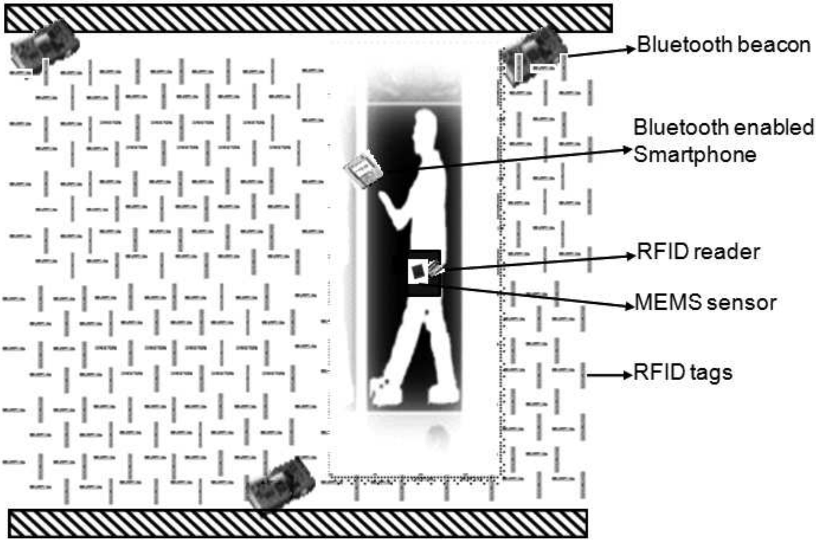

Abbildung 5.1: Experimental setup

the leg pouch which makes it simple for the user to carry and it could be readily integrated with the future′s mobile phones. In this section the detailed information about the different hardware is discussed.

5.1.1 BTnode

The Bluetooth part of the experimental setup consists of BTnodes [1][Figure 5.2] as beacons and a Bluetooth enabled mobile phone. The BTnode is an independent wireless platform for communications and computing. Moreover, it is the prototyping platform in mobile and ad-hoc connected networks (MANETs) and distributed sensor networks. The BTnode has been jointly developed at ETH Zurich by the Computer Engineering and Networks Laboratory (TIK) and the Research Group for Distributed Systems. The BTnode system consist of the ATMEGA 128 L microcontrollers, 32 KHz real time clock and 7.3728 MHz system clock and 180 Kbytes low power SRAM. The 4 Kbytes EEPROM and 64 Kbytes SRAM and 128 Kbytes Flash memory of the BTnode enables the user to store additional information. In the experiment the location information of the BTnodes is stored in the EEPROM. The Bluetooth part of the BTnode is made of Zeevo ZV4002 Bluetooth radio and a

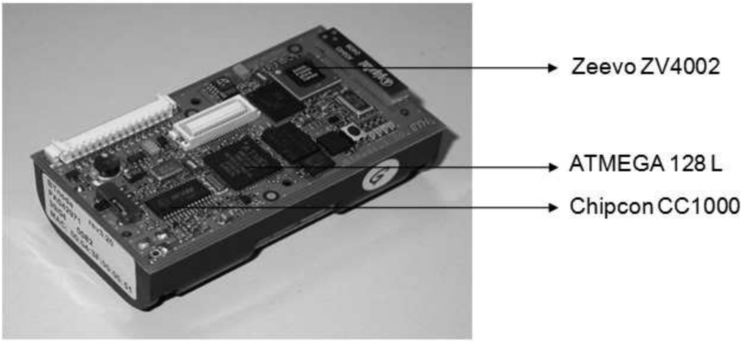

Abbildung 5.2: BTnode

chipcon cc1000 low power radio.

The characteristic of Zeevo ZV4002 such as low cost, compactness, flexibility and less power consumption makes it ideally suitable for a wide range of applications. The radio is of the power class 2 and has an operating range of 10m. It operates with 3.3 v power supply. Since it adapts the selective frequency hopping (SFH) algorithm in addition to Adaptive frequency hopping (AFH) it enables faster connection establishment between Bluetooth 1.2 and 1.1 devices. It can support up to 4 independent piconets and 7 Slaves. The experiments are carried over with the Zeevo ZV4002 radio. The additional Chipcon CC1000 is a low-power radio operating at 868 MHz with an internal antenna. The BTnode is about 58.15x32.5mm in size. The BTnode supports both the Nut OS and TinyOS and comes with BTnut software for programming. The software part for the proposed Bluetooth localization system is based on the Nut OS and BTnut system software.

These BTnodes serves as the beacons for the proposed localization system and is installed in the environment. Generally the beacons can be placed at any desirable height. In the proposed scenario, the experiment is carried out by placing these beacons on the floor. On the other hand, the master node that is used for the experiment is the Bluetooth enabled smart phone with enhanced data rate (EDR) which enables fast connectivity required for localization application.

5.1.2 A528 UHF RFID Reader

Abbildung 5.3: A528 UHF RFID reader and Higgs-2 tags

In the experimental design, the RFID reader used is the short range device, CAEN′S A528 OEM UHF RFID reader [Figure 5.3].The A528 [2] is an OEM UHF multi-regional compact RFID reader for integration into label printers, label applicators, handheld devices and in general any fixed or mobile short and medium range device requiring UHF tag programming and reading. It solves the proximity problem of the RFID reader to the transponder and manages to read the transponders at 1.5m distance. Moreover, it remains appropriate for applications where compactness remains a vital feature. The A528 RFID reader can operate in both European (ETSI EN 302 208) and US (FCC part 15) regulatory environments. Due to its multiregional capabilities the A528 RFID reader is ideal for integration into devices requiring compliance to any geographic regions. It is programmable up to 500 mW conducted power. The RFID reader supports EPC Class1 Gen2 protocol. The module uses the Intel UHF RFID Transceiver R1000 and features a Gen2 dense reader Mode capability. The RFID reader is provided with USB and UART support. The RFID reader supports different modulation and link profiles according to EPC class 1 GEN 2 protocol. The RFID reader allows user to manage host communication through two different protocol such as CEAN communication protocol and INTEL communication protocol. In case of CEAN communication protocol the host reader interface is the UART, whereas in the INTEL communication protocol it is the USB.

The power adapter can have a maximum current rating from 1 A to 1.5 A. The RFID reader is (42 x 60 x 6.3 mm$\hat{3}$) in size and weighs 16 g. The antenna employed for the RFID reader is WANTENNAX008 which is a compact bent dipole linearly polarized antenna that supports the European UHF RFID band and houses a RG 178 cable equipped with a MMCX male connector. This antenna can be used for testing purposes or as an embedded antenna for usage inside RFID handheld devices. The antenna is of compact size (55 x 45 x 0.5 mm$\hat{3}$) and has 0.8 dBi gain.

The transponder that is used for the experiment is the Alien′s Higgs-2 tags [Figure 5.3]. The Higgs-2 tag [6] is a highly integrated single chip UHF RFID Tag IC which conforms to the EPC global Class 1 Gen 2 specifications. The tag provides state-of-the-art performance for a broad range of UHF RFID tagging applications. Higgs-2 operates at extremely low power levels yet still provides sufficient backscatter signal to read tags at extended range. Higgs-2 can also be programmed at low RF power and, in conjunction with a custom command, be programmed at high speed. Higgs-2 is implemented in a low cost CMOS process and uses proven and cost effective EEPROM technology. Higgs-2 features 4 unique memory maps that allow the IC to be tailored for different applications and use cases, 192-Bits of Nonvolatile Memory configurable in 4 different memory maps such as 96-bit EPC (32-bit Access and 32-bit Kill Passwords), 96-bit EPC (32-bit Unique TID, 32-bit Kill Password), 96-bit EPC (64-bit User) and 128-bit EPC (32-bit Kill Password). It has an optional pre-programming with a unique, unalterable 32-bit serial number and supports all Mandatory and Optional Commands except for Block Erase/Write. It operates at low power for both read and program and has a long operating range, up to 10m with appropriate antenna. These tags are placed on the floor with a distance of 50cm between each both horizontally and vertically.

As a communication interface to the mobile phone a BTnode by ETH Zurich [1] is used. The RFID reader is connected to the BTnode through UART interface. The RFID reader along with the communication interface is placed in the leg pouch in order to be in proximity to the transponders.

5.1.3 HMC6343 3D Compass

The IMU consists of the Honeywell HMC6343 3- axis compass module [4] with tilt-compensation algorithms [Figure 5.4]. It comes with a firmware capable of heading computation and calibration for magnetic distortions. It combines 3-axis magneto-resistive sensors and 3-axis MEMS accelerometers. The module has an integrated microprocessor for computation of heading information and tilt-compensation and features analog and digital outputs. It just occupies 9 x 9 x 1.9 mm of space and

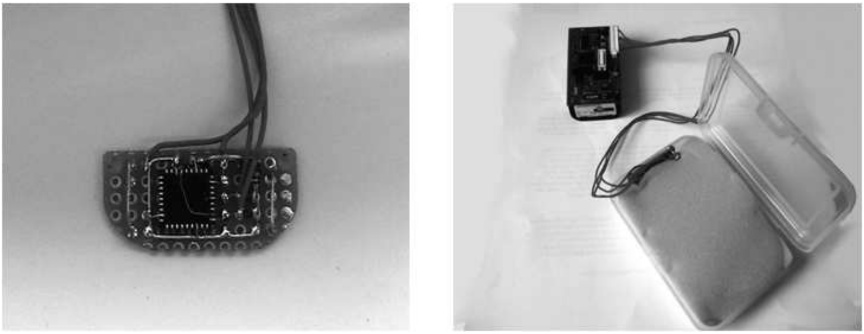

Abbildung 5.4: HMC6343 Compass module and PDR system

has a standard voltage of 3.3 V. With this low operating voltage it is compatible with battery powered applications and therefore predestined for wearable computing environments. The compass module utilizes a special magneto-resistive technology by Honeywell and features a solid-state construction with very low cross-axis sensitivity.

The HMC6343 also features a complete compass solution with integrated compass firmware. It outputs heading with an accuracy of 2 degree (and still 4 degree accuracy at a tilt-angle of 60 degrees), pitch and roll information (with 1 degree accuracy each) as well as acceleration values on three axes. The compass module uses a two-wire I2C-Interface for communication and output of data and can be mounted horizontal or vertically.

The Honeywell sensor proves to be an efficient sensor for multiple purposes. The evaluation of the forward acceleration is considered. The sensor also collects acceleration values on both orthogonal axes which can be easily accessed and used for other evaluation purposes.

The HMC6343 also gains compass information on three axes. Besides the orientation values, the PDR system also outputs pitch and roll information. Figure 5.5 and figure 5.6 show typical pitch and roll values for a straight walk. While the yaw values represent the orientation for the system, the roll values represent the rotation around the x-axis and the pitch the rotation around the y-axis. These orientation values are used in aviation to define the position of a plane within its inertial system.

As a communication interface a BTnode by ETH Zurich [1] is used. The Honeywell sensor is connected to the BTnode through I2C interface. The whole IMU is powered by two AA mignon batteries so it benefits from a small form-factor and a light

Abbildung 5.5: Typical Roll-Values occurring during a straight walk

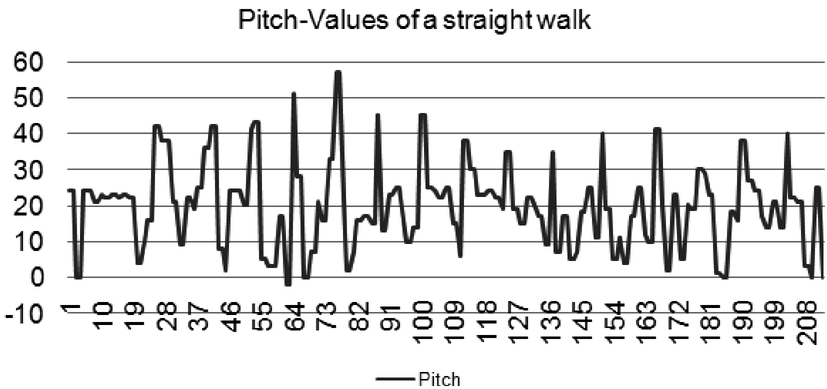

Abbildung 5.6: Raw Pitch-Values during a straight walk phase

weight. Since it uses Bluetooth as communication interface, it can easily be combined with some sort of local positioning system based on Bluetooth nodes to make it a standalone system.

5.1.4 Nokia Smart phone

The Nokia N70 is a smart phone produced by Nokia as part of their Nseries. It has a TFT, 256K colours display with Standard battery, Li-Ion (BL-5C) 970 mAh and 22 MB internal memory. It has Bluetooth version 2.0 with enhanced data rate. The data communication interface to the mobile phone is Bluetooth. However, the phone does not support SVG and to test the navigation application Nokia N95 is used.

5.2 Bluetooth Localization Results

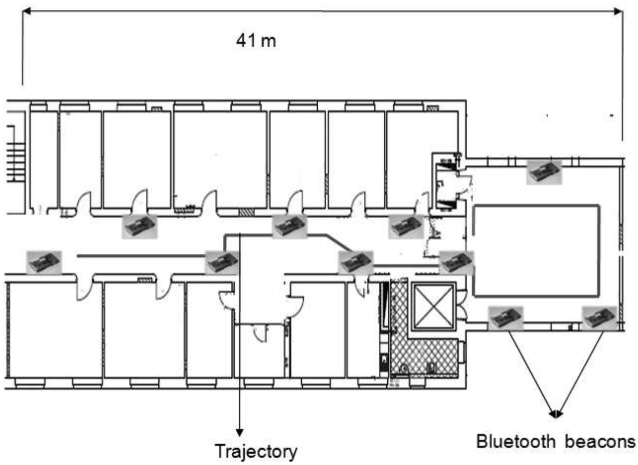

Abbildung 5.7: Example trajectory for Bluetooth localization system

The experiments are carried on the pedestrian path with static Bluetooth beacons installed in the environment. The distance between the beacons varied in each case. The experiments are executed by walking over different trajectories in the pedestrian path. An example trajectory is shown in the figure 5.7.

The test runs are repeated for several times with varying density and trajectory and respective results are presented. Signal strength results and RSSI measures of probability density function are presented in section 5.2.1, whereas the accuracy and reliability measures of the obtained results are justified in section 5.2.2.1. A comparison of accuracy of Bluetooth fingerprinting and MMSE approach to other state of art approaches is being also compared in section 5.2.2.2. Finally, the runtime results of Bluetooth localization approach is presented in section 5.2.6.

5.2.1 Bluetooth RSSI Results

A series of experiment is conducted to inspect the relationship between measured RSSI values and the distance between the fixed Bluetooth beacons and the mobile device. The experiments are performed at both outdoors and indoors. The RSSI values from the Bluetooth beacon are collected repeatedly for an hour by positioning the Bluetooth beacon in a fixed location with varying distance of mobile device to the beacon. The signal strength does not vary much when the mobile is placed in

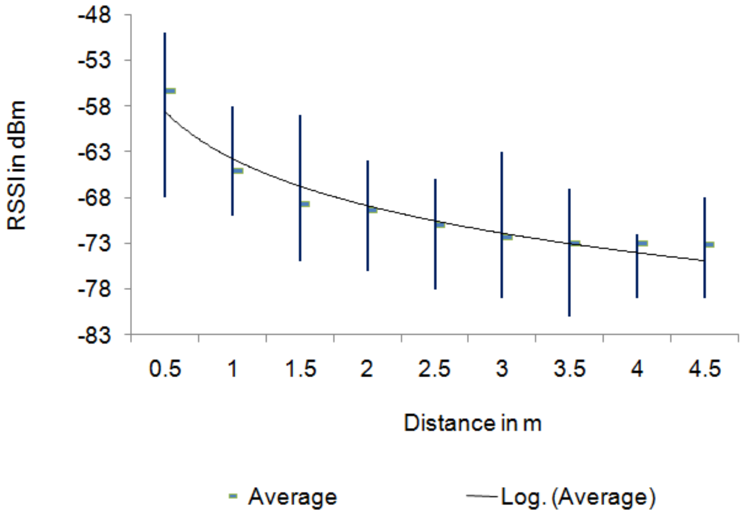

Abbildung 5.8: Distance Vs RSSI

different location at a fixed distance, when tested in outdoor environment. However, in indoor environment signal strength varies in a range with similar distance linking beacon, the mobile device and the location. The variation in the RSSI values at different distance in indoors is summarized in the figure 5.8. The maximum, minimum and the average RSSI value that is obtained at a given distance is shown in the figure. It can be inferred from the figure that the mean RSSI values at different distance vary logarithmically. One cannot estimate absolute distance from the raw sensor RSSI measurement as it is sensitive to noise and other multipath fading. Figure 5.9 shows

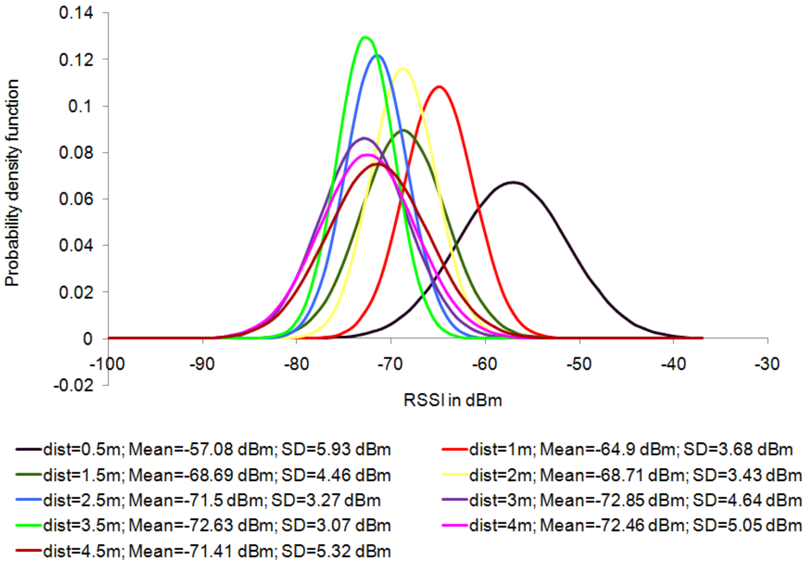

Abbildung 5.9: PDF of the RSSI value at different distance

the normal distribution of the RSSI value at varying distances. The standard deviation (SD) is approximately 4 dBm at each given distance. This shows the deviation in RSSI at different distance from the mean m. This is because; the measurement obtained is influenced by the sensor noise. Thus, one cannot estimate the accurate position of the user without using filtering algorithm.

Figure 5.10 shows the probability density function of the distance values with different RSSI. The mean is at the peak of the distribution. It could be inferred, that the mean of the distance increases with the decreasing RSSI value. For this demonstration the numbers of frequency of distances are calculated for given RSSI values from -52 dB to -74dB. In this interval the standard deviation is increasing from 1cm to 90cm. Based on the observation from the preliminary experiments, it is sensible to set the standard deviation in the particle filter in the equation 4.7 to a value of 0.2*d. Where d is the distance calculated between the beacon coordinates and the estimated coordinates from the Bluetooth fingerprinting.

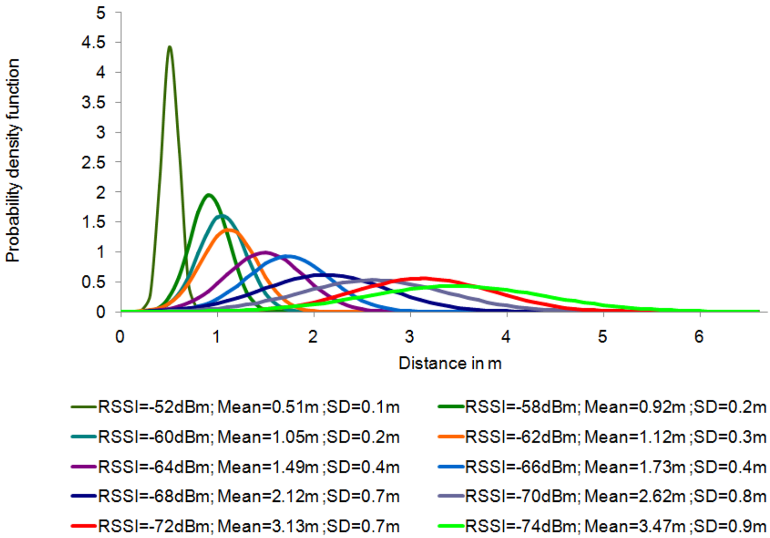

Abbildung 5.10: PDF of distance values with different RSSI

5.2.2 Estimation of Localization Accuracy

5.2.2.1 Localization Accuracy of Proposed Bluetooth Approaches

The accuracy of the localization approaches MMSE and Bluetooth fingerprinting is evaluated by repetitive experiments carried out at a varied walking pace, a different starting point and employing different density of Bluetooth nodes. The Bluetooth beacons are placed at a distance of 2m, 3m, 4m and 5m between them in each test run. In each localization run, the mean absolute localization error is measured. The mean and standard deviation of the localization accuracy are shown in figure 5.11. It could be visualized that Bluetooth fingerprinting approach has a mean localization error around 1.29m, whereas the MMSE approach has a mean localization error of 1.21m. However, the standard deviation of MMSE varies much compared to the Bluetooth fingerprinting. This is due to the fact that MMSE approach depends on the grid points used in the algorithm. The lesser the distance between the grid points, the low is the error rate. The particle filter based Fingerprinting approach utilizes the information gained previously and predicts the next step from the sensor measurement. Therefore, the reliability and accuracy is elevated in case of Bluetooth fingerprinting

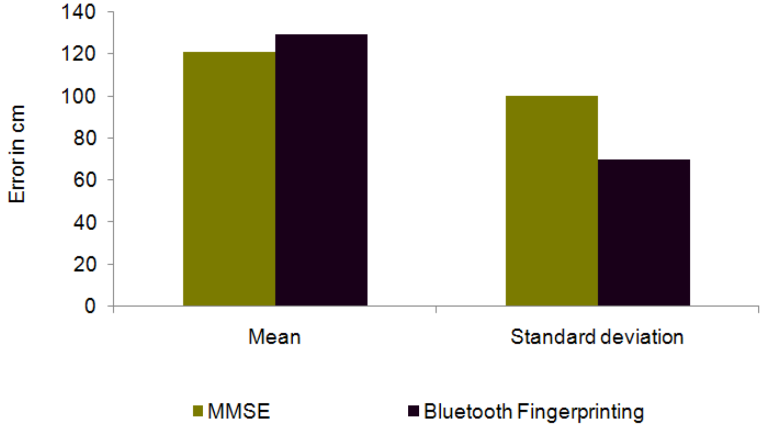

Abbildung 5.11: Mean and standard deviation of the localization error

approach.

5.2.2.2 Comparison of Accuracy of Proposed Bluetooth Approaches with State of the Art Approach

Experiments are carried over to compare the Bluetooth fingerprinting and MMSE with the state of the art approach by executing the same in the testing environment. The results shown in the table are obtained with the density of the beacons set at 1 per 4m. The comparison of all three approaches yielded estimation errors in its worst case of about 7m in KNN, 5m in MMSE, 4m in the Particle filter based on Bluetooth RSSI fingerprinting. In the average case, the Bluetooth fingerprinting and MMSE approach is 1.2m with the best case behaviour as approximately 10cm. However, the MMSE is not reliable compared to the Bluetooth fingerprinting approach. Table 5.1

Tabelle 5.1: Localization accuracy of Bluetooth approaches in cm

Accuracy level	KNN	MMSE	Bluetooth fingerprinting - Particle filter
Best case	120	20	6
Worst case	743	504	409
Average	264	121	129

summarizes the localization error obtained by executing the localization approaches.

5.2.3 Reconstruction of Trajectory with Proposed Bluetooth Approaches

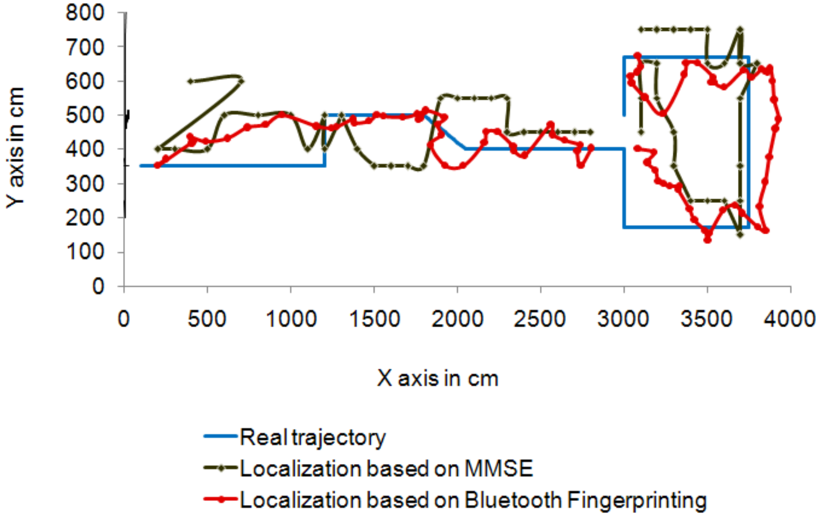

Abbildung 5.12: Reconstruction of trajectory with Bluetooth approaches

The experiments are carried over reconstructing the trajectory from the localization result. Figure 5.12 shows the trajectories reconstructed from the MMSE and Bluetooth fingerprinting approach for one of the real trajectory. The density of the Bluetooth beacon in this case is 1 per 4m. It could be visualized from the figure that both the approach can reconstruct the trajectory, though it doesn't match the real trajectory exactly. However, it could be seen from the figure that the Bluetooth fingerprinting approach could remake the trajectory better than the MMSE approach. It could also be visualized from the figure that there is an interruption in service around 2800 - 3000cm. The Bluetooth based localization can be used for all application which could work well with the coarse grained accuracy. Considering the reliability of localization, the experiments by then are carried over with the Bluetooth fingerprinting.

5.2.3.1 Accuracy of Bluetooth Fingerprinting Approach by Varying the Density of the Bluetooth Beacons

Accurate distance measurement is obligatory to transfer object coordinates into a data processing system in real time for visualization. The accurate distance measurement changes with the density factor. However, the experiments are performed considering density of the Bluetooth beacons installed in the environment.

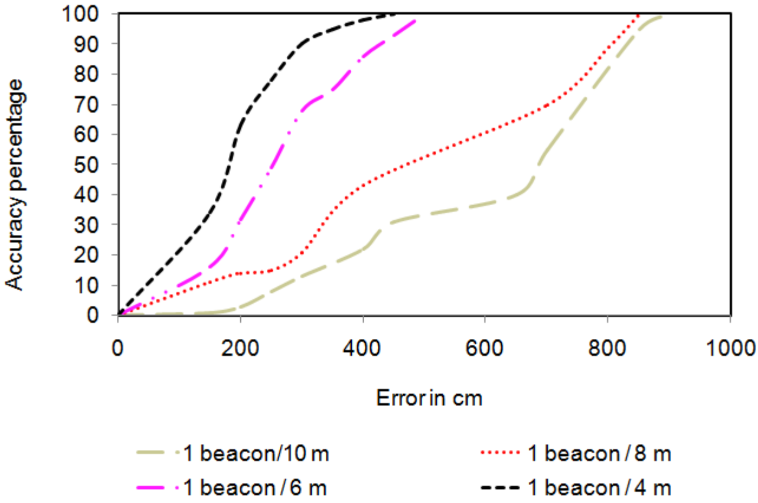

Abbildung 5.13: Accuracy by varying the density of Bluetooth beacons

Figure 5.13 depicts the accuracy factor in relation to the alteration in the density of the Bluetooth beacons. The accuracy of the localization turned out to be worse with less Bluetooth node density. For instance, an user can get connected maximum to 2 beacons when the density of the beacon is 1 per 8m as the range of the Bluetooth is restricted up to 12m. Larger the density of the Bluetooth nodes, the accuracy is higher. However, it is not cost efficient to install Bluetooth nodes per 2m or 4m.

In order to compromise between the accuracy and the cost efficiency the best installation would be 1 Bluetooth beacon per 6m.

5.2.4 Reliability of Bluetooth Fingerprinting Approach

Figure 5.14 shows the reliability percentage of accuracy level of Bluetooth localization with the beacons installed 1 per 6m. The figure 5.14 surmises that the Bluetooth fingerprinting approach guarantees an accuracy level of 5m 100% of times. However, 68% of times it attains the accuracy of 3m and 32% of times it can attain an accuracy of 2m. One can rely on the 4m accuracy from the Bluetooth fingerprinting approach 86% of times. The reliability is best achieved by arrangement of the beacons on both side of the pedestrian path.

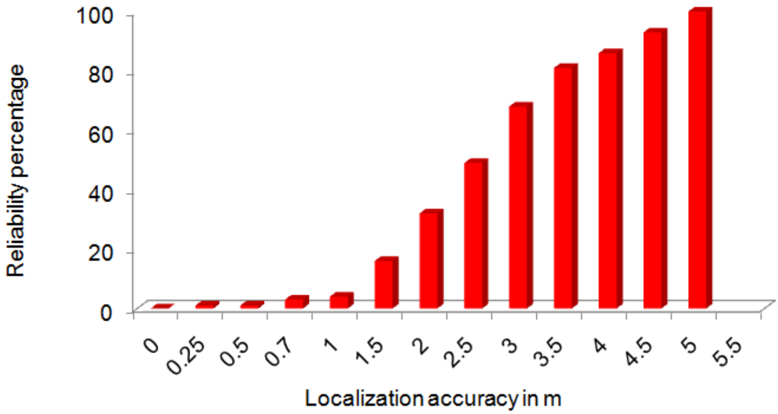

Abbildung 5.14: Reliability of Bluetooth fingerprinting approach

5.2.5 Robustness of Bluetooth Fingerprinting Approach

Experiments are executed to examine the robustness of Bluetooth at indoors with an environment variation with beacons installed 1 per 6m. Test runs are performed with up to 10 users moving around in the measurement environment and test runs are executed without any user as well. These test runs are also performed in the presence and absence of obstacles.

Figure 5.15 shows the accuracy level of Bluetooth with varying environment as explained above. Though Bluetooth require the line of sight for the noiseless measurement, the arrangement of the beacon in the environment does not change the

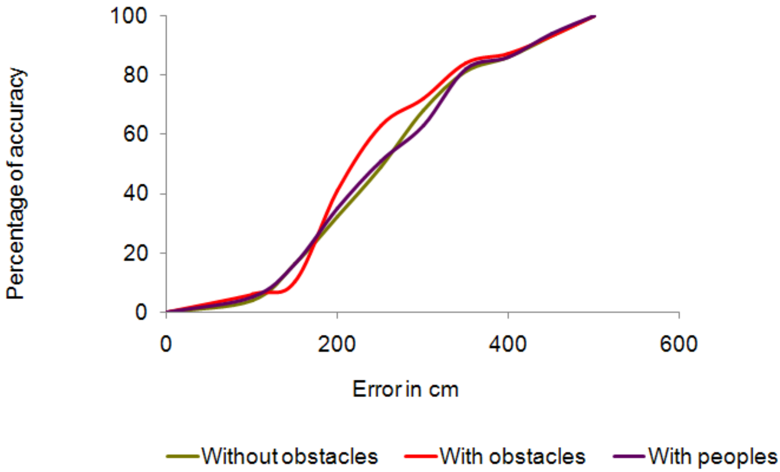

Abbildung 5.15: Robustness of Bluetooth fingerprinting approach

accuracy level much with the changing environment. The worst case accuracy of the system does not vary with users or obstacles, whereas the average case accuracy varied slightly with obstacles but not with users.

5.2.6 Scalability and Runtime of Bluetooth Fingerprinting Approach

Inquiry done in Bluetooth is a onetime process and the time required varies from 12.8s to 28s, whereas the paging time varied from 700ms to 14s. The paging time will remain maximum, if Bluetooth node is placed remote. Occasionally, the Bluetooth node placed in closer proximity to Bluetooth master cannot be paged soon. However, the roaming algorithm tries to page up the Bluetooth node for a second and if it fails, it tries to page the next Bluetooth nodes. This facilitates to establish the connection to at least one Bluetooth node. Exceptionally, the master cannot page to Bluetooth beacon at a maximum of 1.24s which would result in interrupted service for 1.24s. The time for requesting and receiving the absolute RSSI value is approximately 150ms. While the time taken for the particle filter is approximately 1.7s.

5.3 RFID Localization Results

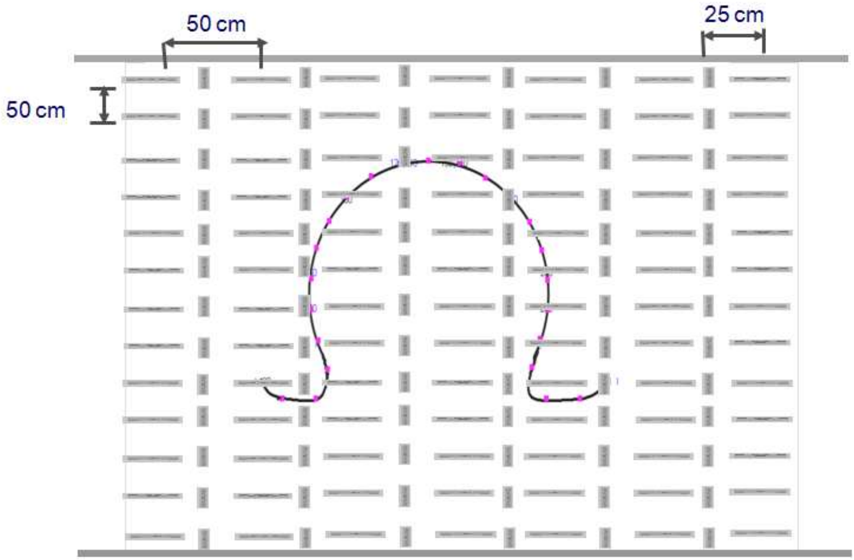

Abbildung 5.16: Experimental setup - RFID

The experiments to investigate the localization accuracy of the RFID system are carried out in the small area of the pedestrian path since the range of RFID is 1.5m. Tags are assigned 50cm apart both horizontally and vertically, whereas the distance between horizontal and vertical tags remained 25cm apart. A grid of 300 x 600cm is used. The tag distribution and an example trajectory over which spots are superimposed are shown in figure 5.16. Readings are obtained over these spots when moved through the multiple trajectories.

In this section, the ability of the RFID reader to read the tag by stepping up and stepping down the power is investigated followed by the tag count and RSSI graphs. The estimation of the accuracy of the RFID localization based on the three proposed localization approaches is described. The summary of the localization accuracy of the RFID systems is presented followed by the reliability of RFID system and finally comparing the same with the RFID based state of art approaches.

5.3.1 Read Range Obtained by Stepping Up /Down the Power

Experiments are conducted in order to test the maximum transmitting power that the RFID reader needs to detect the tags. The maximum power output of the RFID reader is 500 mW. The RFID reader can be programmed in 8 steps based on output power. By stepping up and down the output power, the reading range of the RFID reader is examined. In all experiments the RFID reader is placed at the height of 50cm above the ground level. The maximum reading range obtained in each power state is summarized in table 5.2.

Tabelle 5.2: Stepping up and stepping down the transmitting power

Transmitting Power Tx in mW	Transmitting Power Tx in dBm	Read range incm
25	13.9	0
50	16.9	10
75	18.7	15
100	20	66
200	23	66
300	24.7	67
400	26	67
500	26.9	71

It is inferred from the table that when the transmitting power is less than 20 dBm, the RFID reader can read only the tags which are placed at a distance of 15cm. However, when the transmitting power is the maximum i.e. 27 dBm, the RFID reader can read the tag at a distance of 71cm. As the goal is to obtain a reliable and accurate localization; it is obvious that the RFID reader should be capable of detecting maximum number of tags. Therefore, providing maximum power serves the above purpose. However, the increasing reading range with stepping up the power from 13.9 dBm to 26.9 dBm can be used for some application scenario.

5.3.2 RFID RSSI Results

A series of experiments is performed to monitor the behaviour of the RSSI values. The RSSI measures remained imprecise as it is sensitive to noise and effects like shadowing. The median values are depicted across the box plots [Figure 5.17]. Though the RSSI decreases with increasing distance, graph based on the RSSI estimate demonstrated the unreliability if one uses only RSSI measures. It could be seen from

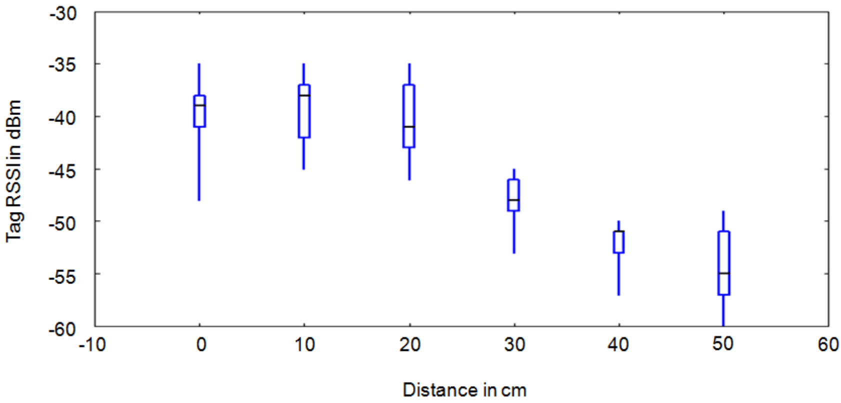

Abbildung 5.17: Distance Vs RSSI

the figure that at each distance there is a variation in RSSI which would reduce the preciseness of the localization system.

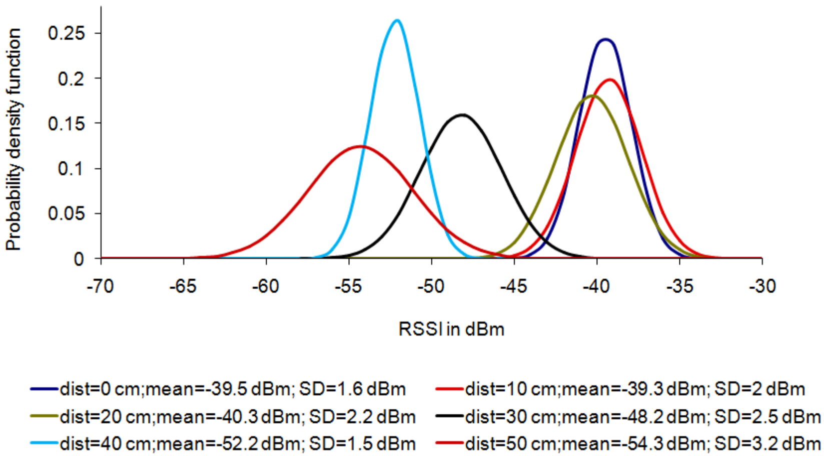

Abbildung 5.18: PDF of the RSSI value at different distance

Figure 5.18 shows the probability density function of the RSSI value at different distances. The probability distribution follows the normal distribution with the mean

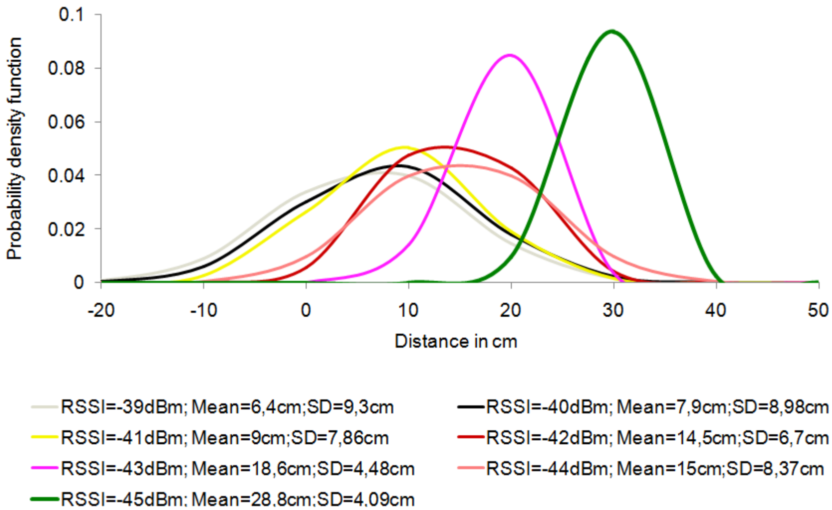

Abbildung 5.19: PDF of distance values with different RSSI

at the peak of the curve and the variance indicating the how the RSSI is strong just about the mean. The standard deviation in each case is approximately 1.1 dBm at the given distance. The figure details that the readings obtained are influenced by the sensor noise. Thus, one cannot estimate the accurate position of the user by only estimating distance out of RSSI.

Figure 5.19 shows the probability density function of the distance values with different RSSI. The mean is at the peak of the distribution .It could be inferred from the figure the mean of the distance increases with the decreasing RSSI value. For this demonstration the numbers of frequency of distances are calculated for given RSSI values from -52 dB to -74dB. In this interval the mean of the standard deviation is 0.6cm. Based on the observation from the preliminary experiments, it is sensible to set σ in the particle filter(Equation 4.13) to a value of 0.6m. Since the tag count variation is not much the value of σ in the equation 4.9 is set to 0.2m. In case of cohered approach the σ in the equation 4.16 is set to 0.24cm (based on preliminary experiments) since the variation in calculated distance is much less.

5.3.3 Estimation of Localization Accuracy

5.3.3.1 Localization Accuracy of Proposed RFID Approaches

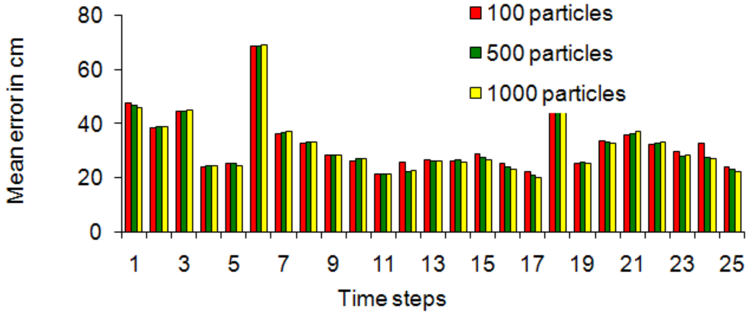

Abbildung 5.20: Mean localization error of RFID tag detection count approach

Further to determine the accuracy of the RFID localization approaches, experiments are executed by walking over the trajectory several times with different starting point and at different tag orientations. With the obtained readings, RFID based approaches described in section 4.3 are evaluated.

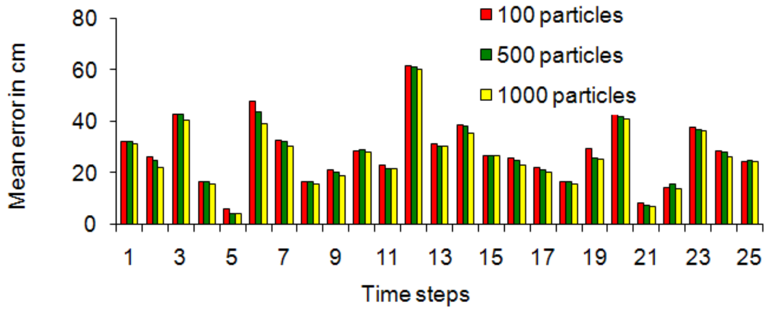

Abbildung 5.21: Mean localization error of RFID RSSI approach

In each of those described approaches, particle filter is executed several times considering the random nature of particles. Mean localization errors i.e., the average localization error by several measurements are determined over different time periods for each of those approaches. The mean localization error in each of the approach is shown in the figure 5.20 - 5.22.

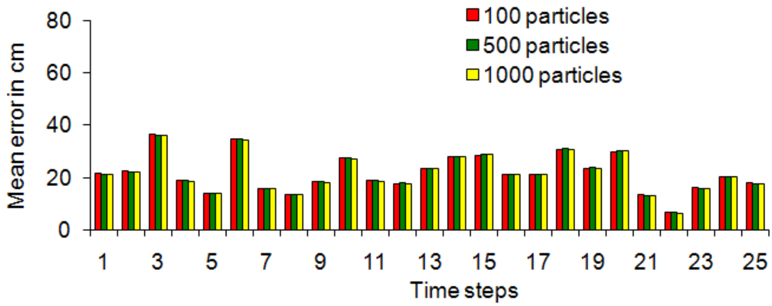

Abbildung 5.22: Mean localization error of RFID cohered approach

The results show that cohered algorithm provides higher accuracy compared to the single solution based on tag count or RSSI values. Nevertheless, the behaviour of the localization algorithm with changing number of particles in the particle filter is tested. However, the test yielded no difference in estimation errors for 100, 500 or 1000 particles used. From the observations, usage of 100 particles is sufficient to obtain an optimum result. Without considering laser scan or odometry data as in Haehnel′s [32] and snapshot [39] approaches respectively, the proposed approach yields very low localization errors when compared. Runtime of particle filter remains almost same 7.3msas in the snapshot approach, however better than in Haehnel′s approach. The best opted cohered approach is used for further localization estimation.

5.3.3.2 Comparison of Accuracy of Proposed RFID Approaches

The comparison of the all three approaches yielded estimation errors in its worst case of about 68cm in tag count based localization [section 4.3.1.1], 64cm in RSSI based localization [section 4.3.1.2] and 35cm in the cohered approach [section 4.3.1.3].

The results are summarized in table 5.3. The results depicted in table 5.3 substantiates that the localization approach is highly reliable with improved accuracy when compared to others. When compared to other approaches at its average case, cohered localization approach attained an error rate around 21cm in comparison to other tag count approach(32 cm) and RSSI based approach(27 cm). Moreover, the reliability of the cohered approach is high compared to the other approaches. The experiments by then are carried over with the cohered approach.

Tabelle 5.3: Comparison of RFID based localization approaches

Accuracy level	Measurement based on		
	Tag count	RSSI	Tag count and RSSI
Worst case	68cm	61cm	35cm
Best case	21cm	6cm	5cm
Average	32cm	27cm	21cm

5.3.4 Reconstruction of Trajectory with Proposed RFID approaches

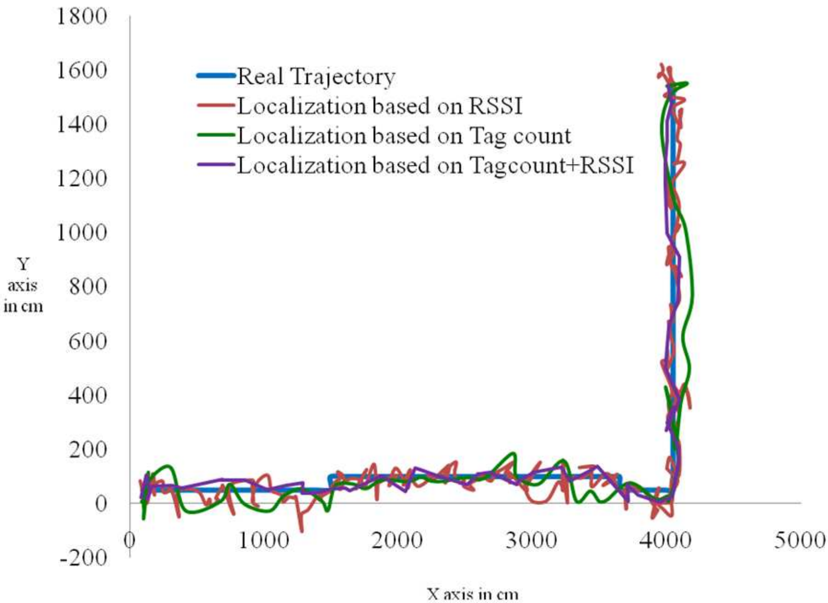

Abbildung 5.23: Reconstruction of the trajectory with RFID approaches

Experiments are carried over to test the ability of the system to reconstruct the trajectory from the measurement data. Figure 5.23 shows the reconstruction of one of the trajectory. The trajectory is reconstructed with all three approaches as described in section 4.3. It could be seen from the figure all the three approaches are able to reconstruct the trajectory without any interruption in service. However, a closer look at the figure shows that cohered approach outperforms the other two approaches. The

RSSI based approach shows a large deviation to the real trajectory because of the variation in RSSI. Since the cohered approach works with the combined tag count and RSSI measurement it is able to eliminate the false readings and construct a trajectory closer to the real trajectory.

5.3.4.1 Accuracy of the RFID Cohered Approach by Varying the Density of the RFID Tags

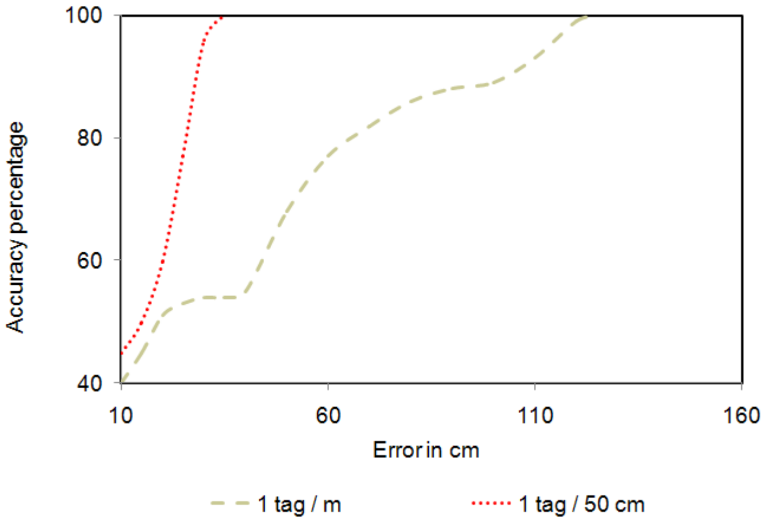

Abbildung 5.24: Accuracy by varying the density of RFID tags

Figure 5.24 depicts the accuracy of the cohered approach with variation in density of RFID tags. The test runs are made with the tags placed at 1 per 50cm and with the reduced tag density of 1 per 1m. The worst case accuracy of the cohered approach is 1.2m when the tags are placed at 1m.

However, the tag detections are null occasionally if the tags are placed at 1m each, as the range of the RFID reader is 1.5m. On the other hand the worst case behaviour of the cohered approach when the tags are placed at 50cm is 35cm. Therefore, to have a precise error correction and to have the tag detection all the time, the RFID tags placed at 50cm each would be a better choice compared to tags at 1m.

5.3.5 Reliability of RFID Cohered Approach

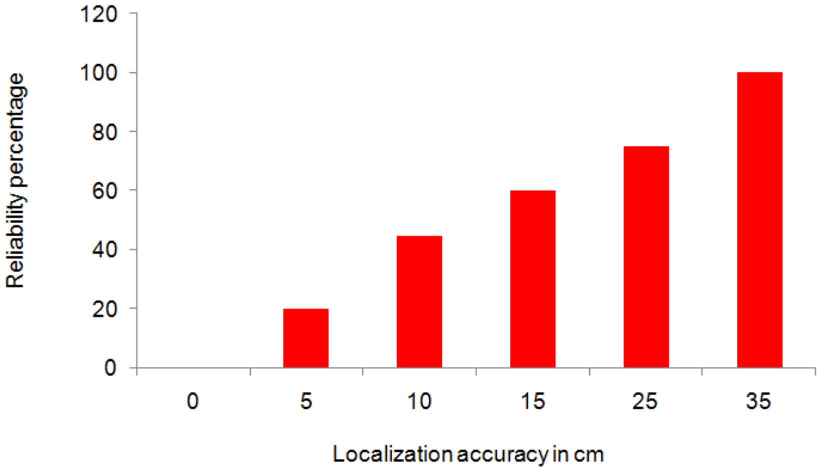

Abbildung 5.25: Reliability of the RFID cohered approach

The reliability of the cohered approach is shown in the figure 5.25.The density of the tag is set to 1 tag per 50cm. It could be visualized from the figure that the cohered approach promises an accuracy level of 35cm 100% of times. The best case behaviour of the approach is 5cm 20% of times with the average case of 25cm 75% of times. This precise localization accuracy of RFID makes it best suited for localization though it lacks the flexibility of installation of tags in the environment. Moreover, it reduces the cost effectiveness of the localization system.

5.3.6 Robustness and Runtime of RFID Cohered Approach

Since the RFID works short range and the localization approach is floor based, the accuracy level doesn′t change with the variation in the environment. The cohered approach is robust enough under all circumstances and is purely scalable. The time taken for the RFID reader to complete the inventory procedure is 235ms. While the time taken by the particle filter to compute the final position with 100 particles is approximately 1.6s.

5.4 PDR System Results

Experiments are carried out by walking over different trajectories on the pedestrian path and accuracy of PDR system is investigated thereby. The ability of the system to reconstruct the moved trajectory is tested followed by the estimation of the localization accuracy of the PDR system by varying the stride length, pace and climbing up/down the stairs. The summary of the localization accuracy of the PDR system is presented and finally comparing the same with the PDR based state of art approaches.

5.4.1 Reconstruction of the Trajectory

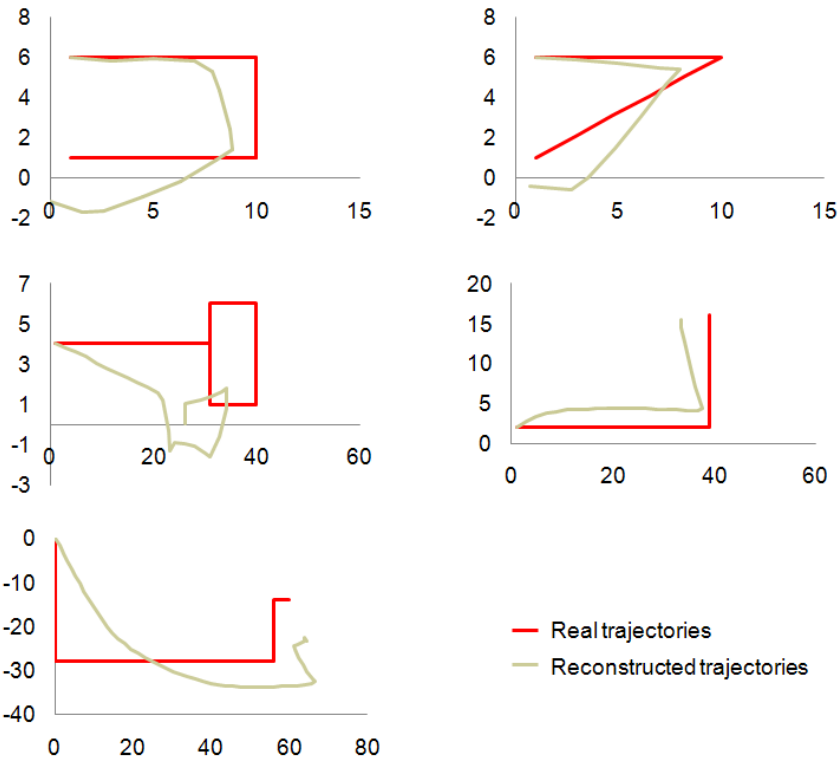

Abbildung 5.26: Trajectory

The experiments performed showed that the PDR is capable of reconstructing the path that is traversed up to an acceptable point of accuracy. The stride accuracy for the trajectories shown below is between 0.5 and 2.5 strides.

However, a look at figure 5.26 shows that the calculated path visibly differs slightly from the anticipated path. This differences is due to the fact that the direction calculations based on several raw direction values are slightly corrupted by the magnetic field of the environment and also the changing position during a stride occurrence (as it is mounted to the user's leg).

However, the results give a satisfactory resemblance of the laid out short distance and long distance trajectories.

5.4.2 Estimation of Localization Accuracy

5.4.2.1 Percentage of False Stride Detection

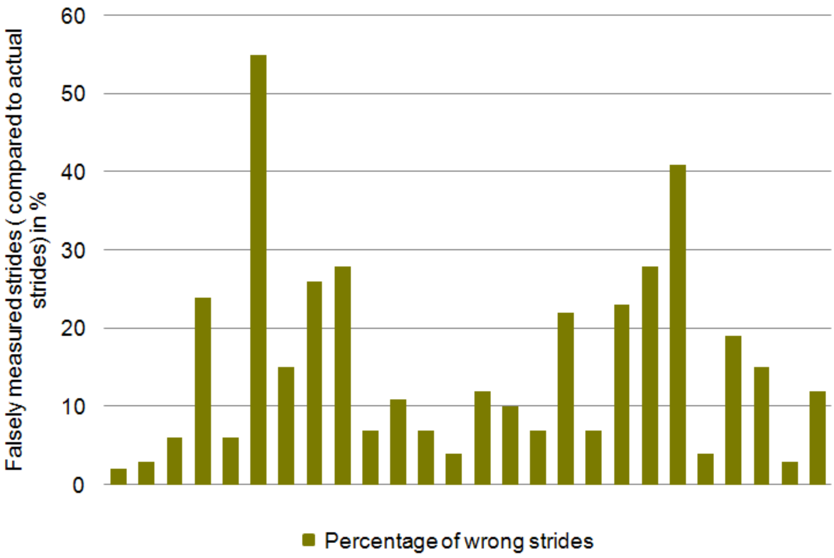

Abbildung 5.27: Falsely detected strides

In all the test runs it is found that the system fails to detect 3.5 strides in its average case. The overall best case is 0.5 missed strides and the worst case is 29.5 strides.

This test run resulted in the worst case scenario as a small stride length is used (See also Section 5.4.2.4). 65% of the measurements had a stride accuracy that is better than the average. 42 % of the runs even achieved an accuracy of more than 93% detected strides, 69 % had a stride accuracy of 81 % detected strides. However, even long distance trajectories always resulted in a stride accuracy of more than 90%.

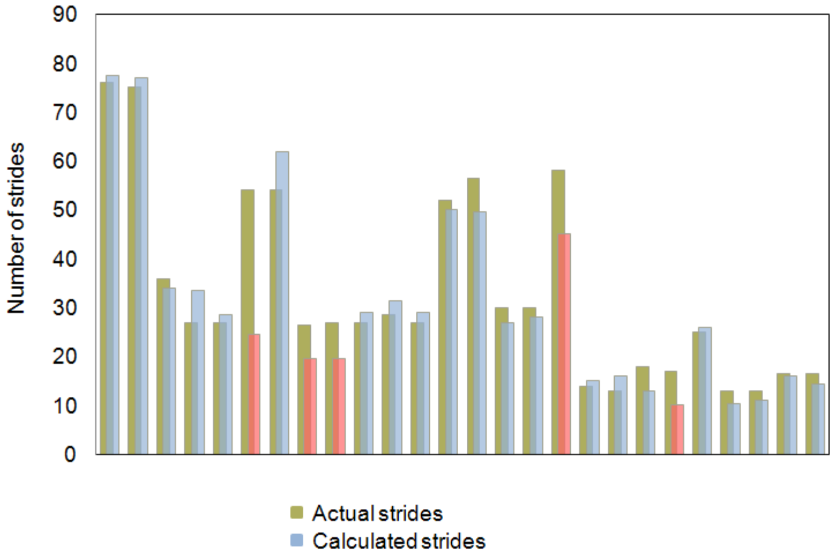

Abbildung 5.28: Comparison of actual and calculated strides

Figure 5.27 and 5.28 show the stride accuracy of several of the test runs. Figure 5.27 shows the percentage of falsely calculated strides. The runs with more than 30 % falsely detected strides are runs with different stride lengths and walking speeds as described in section 5.4.2.3 and section 5.4.2.4. In figure 5.28, a comparison of the actual and the calculated strides for those test runs is shown. Runs with a stride accuracy of less than 80% are marked red. Since the position is calculated for every stride, the mean error at each stride due to the direction variation is 0.4m and the standard deviation is 0.3m. Hence, the σ in the equation 4.24 is set to 0.3m.

5.4.2.2 Mean Error Estimation

To estimate the mean error, experiments are executed by walking over different trajectories several times. Then the mean error is calculated for each of the trajectories. The tests resulted in a mean error of 1.96m as a best result to 11.83m in a worst case scenario where, a path with a distance of 117.75m is traversed. The standard deviation varied between 1.26m in the best case to 4.29m for the long distance trajectory. The mean error and standard deviation results for the five different trajectories above are shown in figure 5.29. The average mean error of all the trajectories is 4.58m.

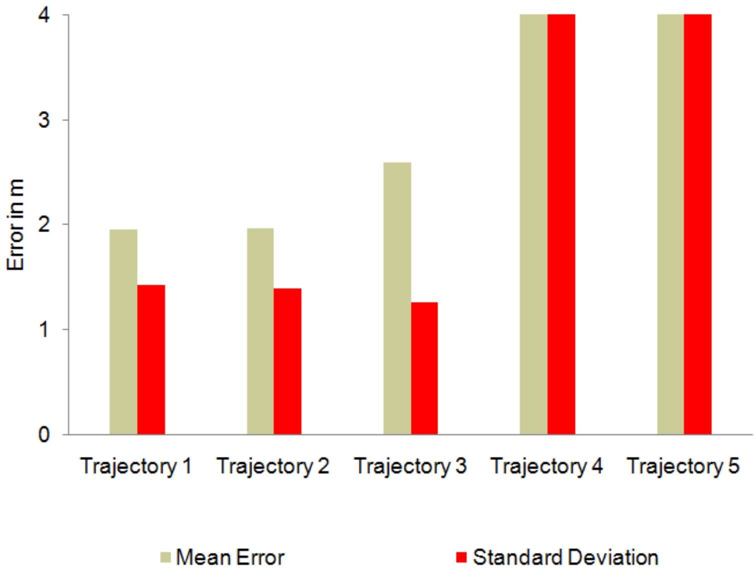

Abbildung 5.29: Mean error estimation

The stride accuracy for the five trajectories described above shows an interesting difference. In the worst case the system fails to detect 2.5 strides with the best case behaviour of missing 0.5 strides. It is clearly visible from the figure 5.29 that the long distance trajectory had a worst case accuracy of 11.8m. So it is concluded that the overall accuracy of the system will decline for very long trajectories, still being far better than an exponential accumulation of error.

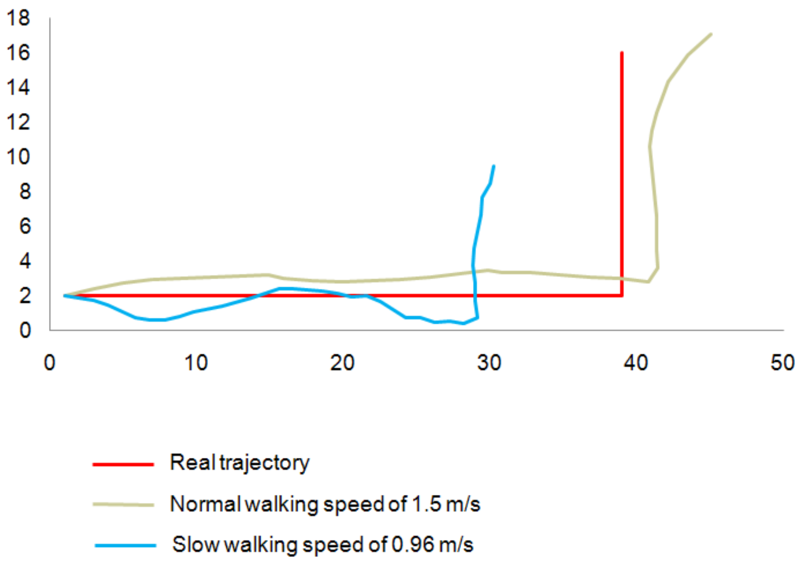

Abbildung 5.30: Localization accuracy by changing the walking speed

5.4.2.3 Localization Accuracy by Changing the Walking Speed

For a closer inspection of the PDR localization algorithm, test runs are carried out with different walking speeds. The algorithm is designed and modelled for a normal human gait. Even in unknown environments very slow walking is unnatural behaviour. But to test the suitability of the algorithm for different walking speeds, experiments are carried out in the different trajectories with different walking speeds. The results are shown in figure 5.30. With a normal walking speed of 1.5 m/s (blue path in figure 5.30), the detection of the path is very precise (94% stride accuracy) while the detection for a walking speed of 0.96 m/s (green path in figure 5.30)) not every stride is detected (72% stride accuracy). However, the calculated path for a more complicated trajectory which delivered a better result and a stride accuracy of 90 % (27 out of 30 strides) is shown in figure 5.30. Comparing several trajectories and several runs, normal speed gives better results than an unnatural slow walking speed due to the design of the algorithm.

5.4.2.4 Localization Accuracy by Changing the Stride Length

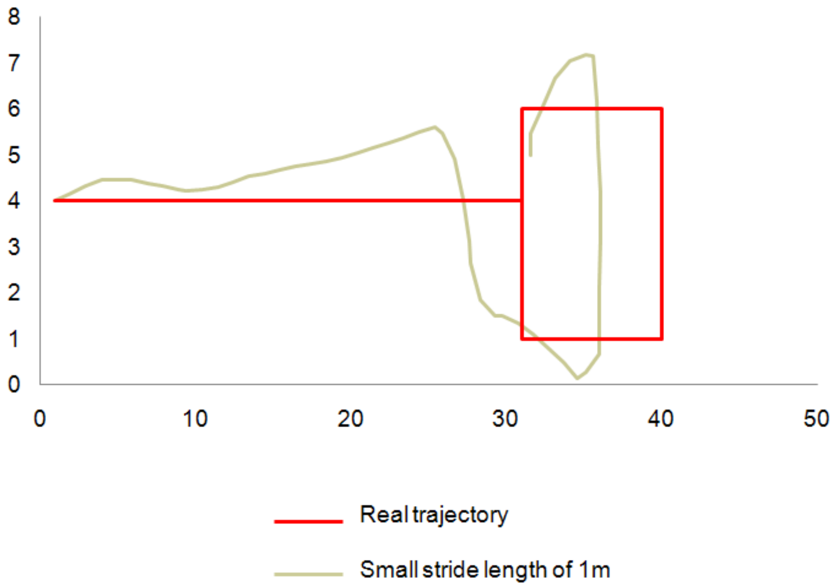

Abbildung 5.31: Localization accuracy by changing the stride length

For further inspection on the algorithm considering not only the walking speed but also the stride length is changed for several trajectories. The normal stride length during the experiments is 2m. With a reduction of the stride length by 50 % to 1m the calculated path from the PDR differed more from the actual path as can be seen in figure 5.31. This behaviour is due to the fact that a stride length of 1m leads to only very subtle movements of the user′s legs during the run. Therefore, the algorithm will result in accurate stride detection. During the experimental phase the reduced stride length led to Tiptoe movement of the user. The calculated path for a more complicated trajectory with a reduced walking speed and stride length is shown figure 5.31. The difference between the actual path and the measurement doesn′t exceed 1.5m on the y-axis and 4m on the x-axis. However, the stride accuracy is at only 78% (45 out 58 strides).

5.4.2.5 Localization Accuracy by Walking over the Stairs

To test the suitability of the system for normal building environments with staircases, some experiments are performed by climbing up and down the staircase. The trajectory consisted of 22 strides in three separate stairs. The paths for the PDR are calculated with a fixed stride length due to the fact that no outside data is available to the system if it is used as a stand-alone application. As the stride length differs between stairs and the intermediate platforms, the strides are detected correctly but the resulting measurement path is either short if a small fixed stride length is used or it is too wide if a normal stride length is used. The results show that the calculated path with a stride length of 2m trails of the actual path by the factor 2, while the calculated path with a stride length of 1m is short in the intermediate section by the factor 0.5 (Figure 5.32).

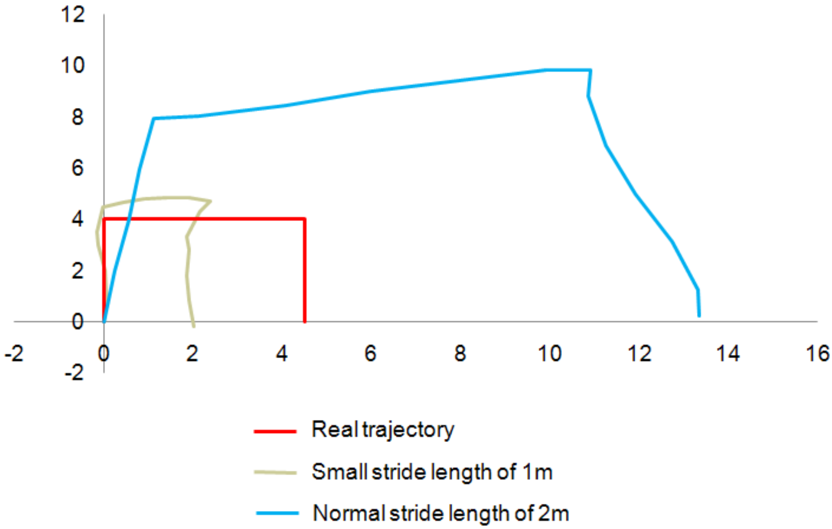

Abbildung 5.32: Localization accuracy by walking over the stairs

5.4.3 Summary of Stride Accuracy

The experimental results for different stride lengths and different walking speeds showed that the PDR algorithm is also capable of coping with different walking styles, but with coarse grained accuracy. However, variations in the stride accuracy occur when the user is not moving within the parameters of normal walking behaviour. This is due to the fact that the PDR system acts as a standalone navigation system and no external data is received to update the PDR and therefore fixed values for stride length and the possible stride time frame are given. As the walking style and therefore the movement of the leg are changed intentionally the algorithm is bound to fail. However, the experiments show that the PDR is even robust to this usage with minor flaws. A comparison of the average stride accuracy and the percentage of when this average is to be expected are shown in table 5.4.

Tabelle 5.4: Summary of stride accuracy

Metrics Metrics		Average stride detection	Accuracy percentage
Changing speed	Normal speed(1.5 m/s)	4.6m	75%
	Slow speed(0.96 m/s)	6.5m	40%
Changing stride length	Normal stride length (2m)	2.9m	69%
	Small stride length (1m)	11.9m	60%
Walking over stairs	Different stride lengths, walking speed of 1.5 m/s	3.6m	60%
Normal stride length normal speed	Stride length of 2m, walking speed of 1.5 m/s	2.2m	75%

5.4.4 Comparison of Peak-Declination and Zero-Crossing Algorithm

A comparison of the designed peak-declination algorithm to the zero-crossing algorithm for a trajectory is made. On an average the proposed PDR system which uses the peak-declination algorithm showed a mean error of 2.2m while the zero-crossing algorithm had 4.5m. The results show that zero-crossing is susceptible to the measurement errors while the system can overcome those problems. The PDR presented here has the advantage of overcoming sensor movement and sensor noise and therefore rectifies the false detection of stride occurrences as the zero crossing algorithm do.

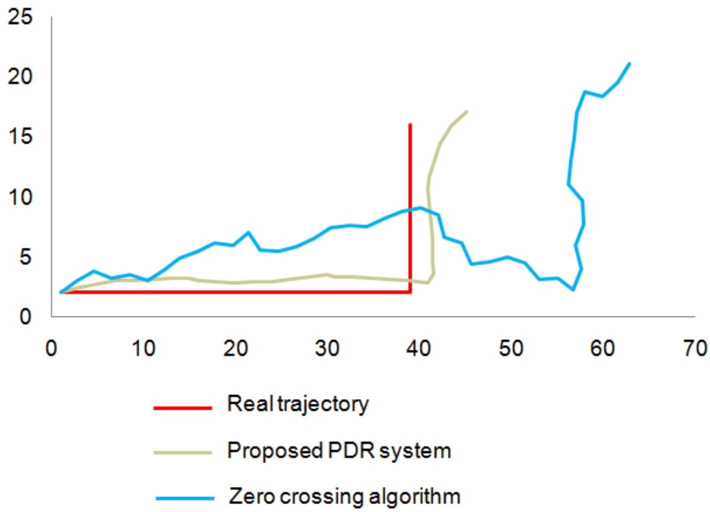

Abbildung 5.33: Comparison of peak - declination and zero crossing algorithm

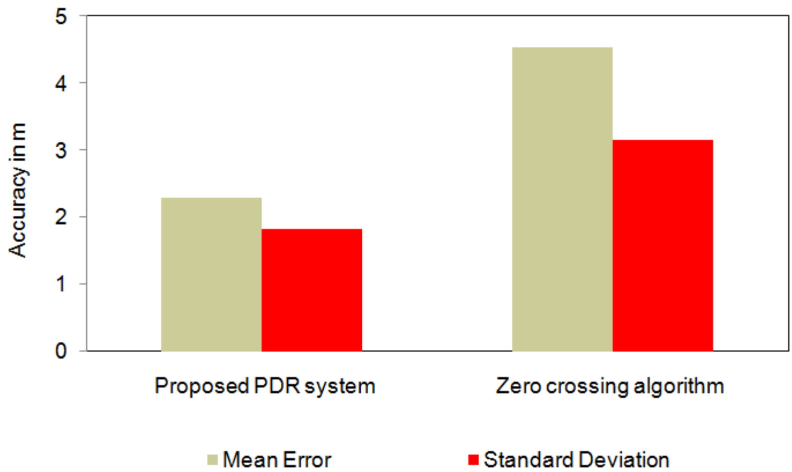

Abbildung 5.34: Mean and standard deviation of localization error

The calculated trajectory for the Peak declination and the Zero crossing algorithm is shown in figure 5.33. The mean and standard deviation over several runs is shown in figure 5.34.

5.5 Results from Hybrid Systems

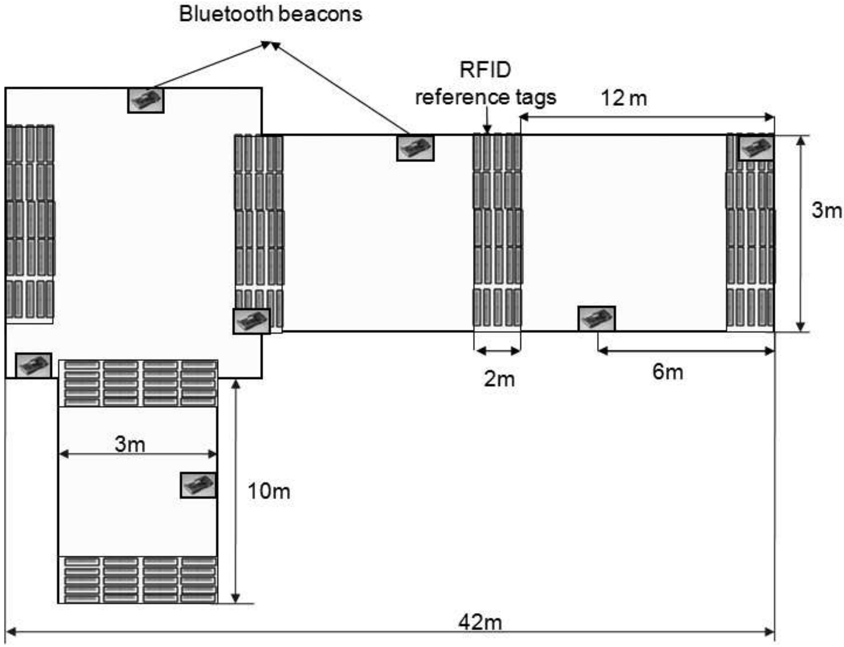

Abbildung 5.35: Experimental setup for Hybrid systems

In order to be cost efficient and flexible, the experimental setup for Hybrid systems is slightly modified by reducing the density of Bluetooth beacons and RFID tags. The BTnodes are placed at a distance of 6m apart, whereas the RFID tags are installed on the floor 50cm apart from each other along certain areas in the pedestrian path. The tag placement is done every 10m. The experimental setup is shown in the figure 5.35.

The experiments are repeated for different Hybrid systems as described in section 4.5 and the mean results are presented. The reliability of the localization system with each of the proposed system is presented.

5.5.1 Localization Accuracy of Hybrid Systems

Experiments are performed to estimate the localization accuracy of the three proposed Hybrid systems: Hybrid BT -PDR, Hybrid RFID - PDR and Hybrid BT - RFID - PDR. The mean localization accuracy and the respective standard deviation for each of the Hybrid systems are presented in the figure 5.36. The mean localization error

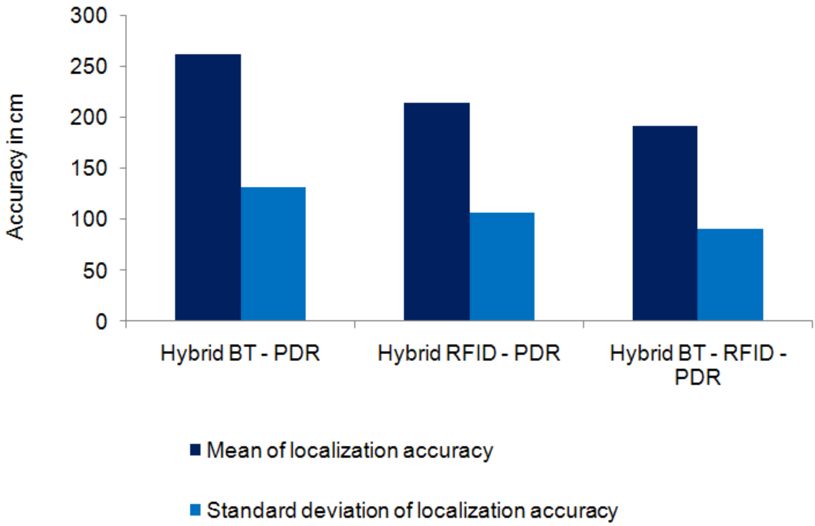

Abbildung 5.36: Mean and standard deviation of the accuracy of Hybrid systems

of Hybrid BT-PDR is 263cm, whereas it is 214 and 191cm in case of Hybrid RFID-PDR and Hybrid BT-RFID-PDR. The better performance of both Hybrid RFID-PDR and Hybrid BT- RFID- PDR is because of the error correction from the RFID localization. The standard deviation of these Hybrid systems are approximately around 100cm. The worst case behaviour of Hybrid BT - RFID- PDR is 350cm which is better when compared to Hybrid BT-PDR and Hybrid RFID-PDR which has the worst case behaviour of 500cm and 400cm respectively.

5.5.2 Reliability of Hybrid Systems

Figure 5.37 shows the reliability of the Hybrid system. The Hybrid BT-PDR had an accuracy of 2.5m, 63% likelihood. However, it can achieve the accuracy of 5m 100%

likelihood. The best case result of Hybrid BT - PDR is 1.5m, 29% probability and 1m, 10 % likelihood. In case of Hybrid RFID-PDR, the localization accuracy of 2m

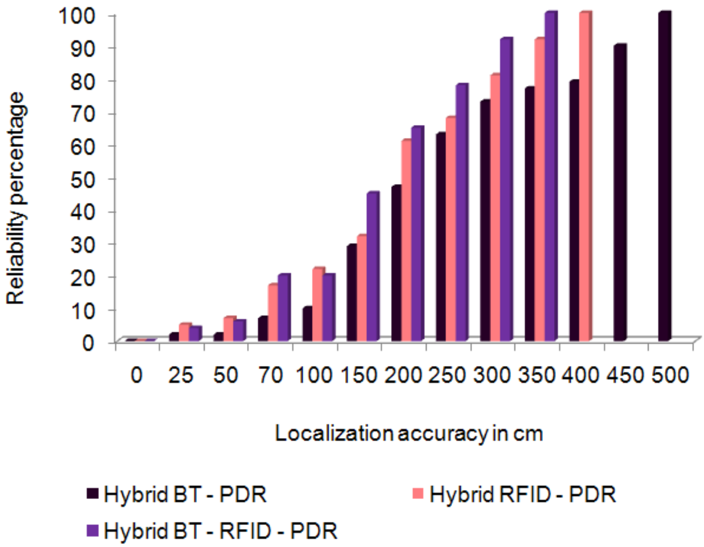

Abbildung 5.37: Reliability percentage of the Hybrid systems

is achieved 61 % likelihood with the best accuracy of 1m and 1.5m achieved 22% and 32% likelihood respectively. In its worst case it could result in the accuracy of 4m, 100% likelihood. With Hybrid BT-RFID-PDR, one can expect an accuracy of 3.5m, 100% likelihood. In its average case it can attain an accuracy of 1.5m and 2m, 45% and 65% likelihood respectively. The overall reliability over accuracy of the Hybrid system is much better compared to the single solution based systems like Bluetooth and PDR.

5.5.3 Reconstruction of Trajectory with Hybrid Systems

Experiments are carried over to check the ability of the Hybrid system to reconstruct the trajectory in which the measurement is made. The reconstructed trajectory from the three Hybrid approaches are shown in the figure 5.38. It could be seen from the figure that the Hybrid system does not provide any interruption in service as do the Bluetooth based localization. Moreover, one could visualize the role of RFID error

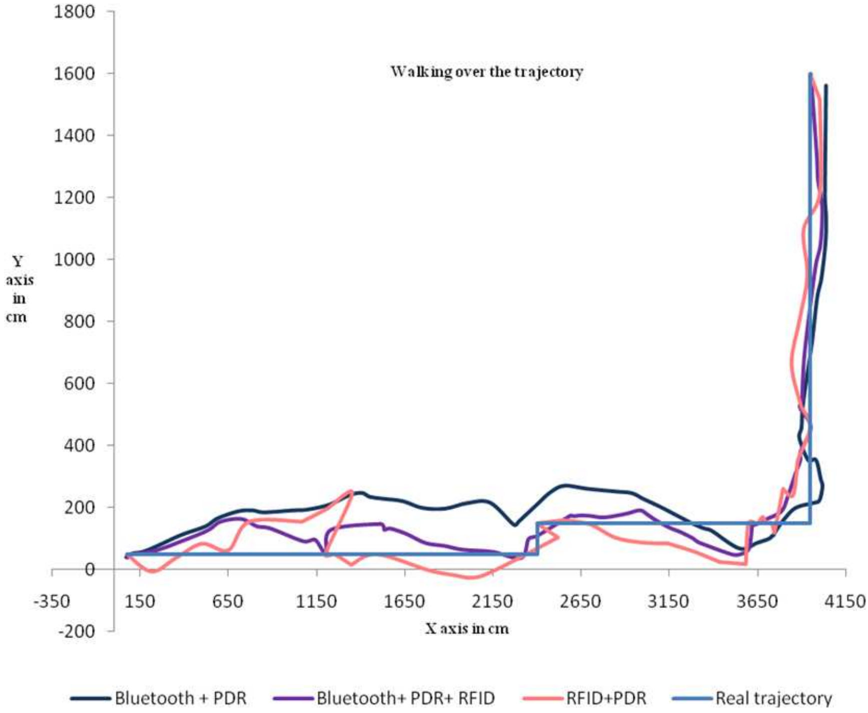

Abbildung 5.38: Reconstruction of trajectory with the Hybrid systems

correction. The trajectory made by Hybrid RFID-PDR evidently explains the error produced by the PDR system (for instance from 100-1200 cm). However, the system proceeds with the error correction done at this point with the RFID system therefore specifying the new starting point (1150,40) for the PDR system. The same holds true for the Hybrid BT-RFID-PDR system. The Hybrid BT-RFID-PDR system has reconstructed the trajectory closer to the real trajectory which shows that it outperforms the other two Hybrid systems.

5.6 Comparison of Localization Approaches for its Efficiency

In order to compare different technologies for localization, decisive factor (described in section 3.6) that a perfect localization system should gratify is considered. The same setup that is used in the section 5.5 is worn to accomplish the experiment. However, when reconstructing the trajectory with RFID only based localization, the experimental setup is altered by installing the tags all over the pedestrian path at a distance of 50cm apart. The experiments are performed by walking over different trajectories in the pedestrian path. Taking into account all factors, the system is graded thus providing evidence for efficient localization system from the end result.

5.6.1 Reliability

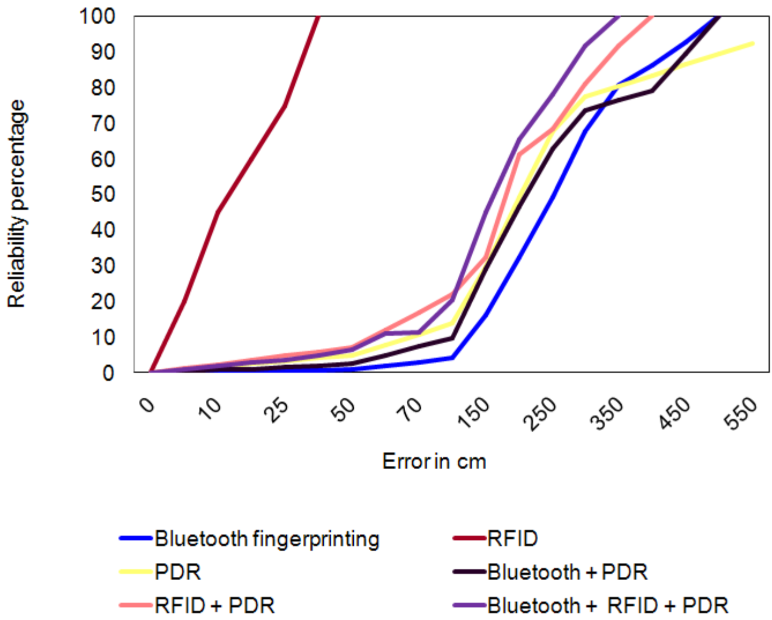

Abbildung 5.39: Comparison of localization systems based on reliability factor

One major aspect for ideal indoor localization is reliability. The Bluetooth based localization had an accuracy of 3m (68% of time). In contrary, RFID based localization provides an accuracy up to 21cm (68% of time), whereas PDR system and the Hybrid RFID - PDR system guarantees a reliability of 2.5m (68% of time). The Hybrid BT-PDR and BT-RFID-PDR can achieve an accuracy of 2.7m and 2.1m (68 % of time) respectively. Figure 5.39 represents the reliability factor across each localization approach. Since the error accumulates with the PDR system, it fails to be reliable. Though RFID based localization is very precise, it is neither cost efficient nor flexible.

5.6.2 Accuracy

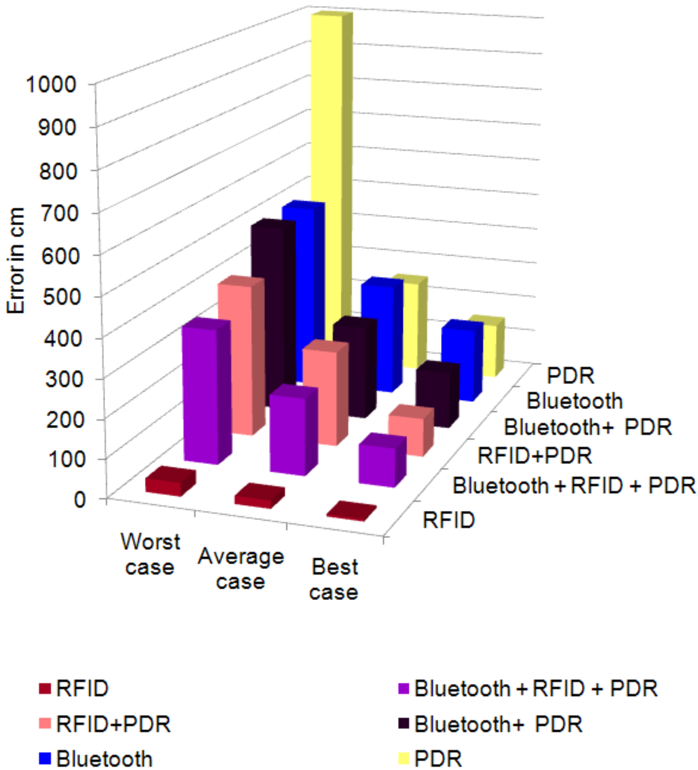

Abbildung 5.40: Comparison of localization systems based on accuracy factor

Figure 5.40 represents the error distribution for various localization systems with the current experimental setup. The mean error value of 2.5m is obtained for all the three approaches employed (Hybrid RFID-PDR, Hybrid BT-PDR, and Hybrid BT-RFID-PDR). The average case is 3m in case of Bluetooth and 2m in case of Hybrid BT-RFID-PDR approach. In its worst case, PDR performs poorer as error accumulates with the distance compared to others. RFID based localization had an accuracy of

21cm on its average case with the worst case behaviour of less than half a meter.

5.6.3 Scalability

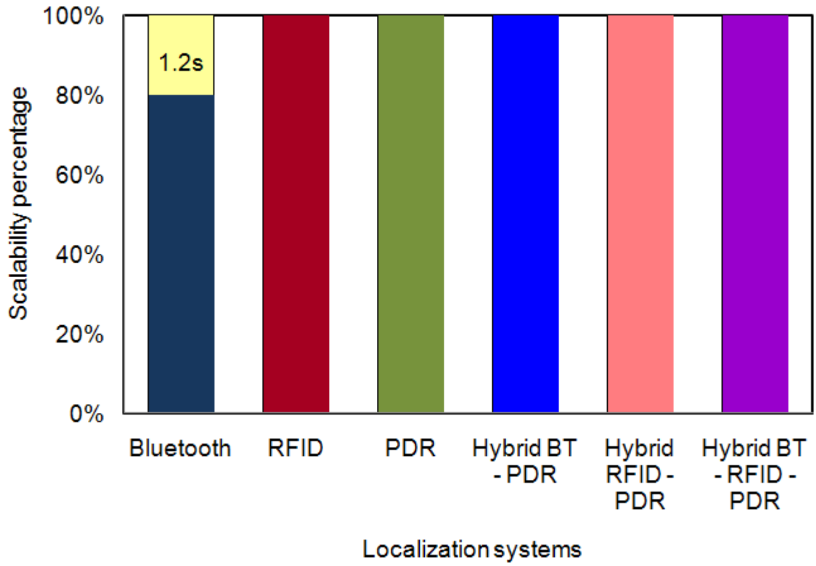

Abbildung 5.41: Comparison of localization systems based on scalability factor

A RFID localization system is highly scalable. RFID sends out short pulses and receives information from the designated tags without continuous connection. RFID tags offer an uninterrupted localization service despite nearly all employed RFID tags is corrupted. On the other hand, PDR as a standalone system provides an uninterrupted service independent of sensors. When it comes to Bluetooth based localization, the Bluetooth master has to be well connected to all Bluetooth beacons within a range of 15m. However, one can end up in an interrupted service when network scaling is performed due to the delayed paging time. Incorporated with the algorithm as described in section 3, Bluetooth could provide scalable uninterrupted service (80% of the time). In its worst case, the service will be interrupted for 1.24s. The solutions based on Hybrid RFID-PDR, Hybrid BT-PDR and the Hybrid BT-RFID-PDR guarantees the scalability as the localization system is able to provide uninterrupted service with any of the coupled scalable sensors. The scalability performance of the localization systems is shown in the figure 5.41

5.6.4 Robustness

Short ranged RFID and standalone PDR remains robust under all conditions and so does the Hybrid system. Since the Bluetooth fingerprinting is made in the indoor building infrastructure which takes into account the noisy measurement, the Bluetooth remains robust with minimal changes irrespective of variation in the environment. The robustness of Bluetooth localization is described in section 5.2. Since all three Hybrid systems are built with the sensors Bluetooth, RFID and PDR, they are considered to be robust too.

5.6.5 Performance

The computation speed of the localization is calculated when the algorithm is executed in Texas Instruments OMAP 1710, 220 MHz processor of the Smart phone Nokia N70. The latency computation algorithm is classified into 3 phases: Setup, data collection and a particle filter phase. The setup phase initiates the segment fraction of the localization system.

For instance, in Bluetooth localization, the Smart phone invokes an inquiry and pages to the located Bluetooth beacons. The maximum time for an inquiry procedure took 12.8s and an average of 1.2s is required to page a single Bluetooth beacon. In case of RFID and PDR, the data collection phase is carried out as there is no setup phase. During the data collection procedure, the Bluetooth beacons measures the signal strength and data is transmitted to a Smart phone. The time consumed for data transmission is between 31 - 43ms. In case of RFID, the RFID reader makes an inventory and acquires data from positioned RFID tags. The time consumed for this single inventory operation is 235ms. Whereas, in PDR the time utilized for the measure of acceleration and direction values from 3D compass is 39ms. Finally, the data manipulation time as needed before the data fed to a particle filter remains 50ms for 3D compass and 20ms for RFID and 10ms for Bluetooth. The execution time for the particle filter is 1.61s per 1000 particles. The computation time in Hybrid scenarios is the combination of the computation time of the single sensor based localization. The Runtime comparison of the localization system is shown in the table 5.5.

Tabelle 5.5: Performance of the localization systems

Runtime /Systems	Bluetooth	RFID	PDR	Hybrid BT-PDR	Hybrid RFID-PDR	Hybrid BT-RFID-PDR
Setup phase	Inquiry BT :12.8s Connection BT :1.2s			Inquiry BT :12.8s Connection BT :1.2s		Inquiry BT :12.8s Connection BT :1.2s
Data collection	43ms	235ms	39ms	82ms	274ms	317ms
Data Manipulation particle filter	1.61s	1.626s	1.62s	1.66s	1.676s	1.676s

5.6.6 Availability

Availability of hardware in Smart phones: Further analysis is performed to check the compatibility of sensors available in today′s Smart phones. This reduces the risk that additional hardware is required for localization. Bluetooth and MEMS sensors are built-in in almost all modern Smart phones and could be employed in real world interactions for localization. The Smart phones available nowadays are equipped

Tabelle 5.6: Availability of the localization systems

Availability /Systems	Bluetooth	RFID	PDR	Hybrid BT-PDR	Hybrid RFID-PDR	Hybrid BT-RFID-PDR
Availability of hardware in Smart phone	Bluetooth: Yes	RFID : No	MEMS : Yes	Bluetooth: Yes MEMS : Yes	RFID: No MEMS : Yes	Bluetooth: Yes MEMS : Yes RFID:No
Availability of service	Dependent on Installation in the environment	Dependent on Installation in the environment	Stand alone	Standalone. Can work without Bluetooth	Standalone. Can work without without RFID	Standalone. Can work without without RFID and Bluetooth

with RFID readers that could not favour the accessing range. The next generation Smart phone is likely built with the UHF RFID readers with the agreeable range and could be efficiently employed in the localization method.

Availability of service to the users: In the case of single sensor based solution like Bluetooth or RFID it is dependent on the setup: Bluetooth beacons and RFID tags respectively. In case of Hybrid systems, it works with the PDR when RFID or Bluetooth connections/beacons are not present. Hence the service is offered to the user in any environment in the Hybrid solutions.

5.6.7 Cost Efficiency

The installation cost for localizing the system is calculated per square meter. It could be seen from table 5.7, the total cost of installation of all Bluetooth based systems is priced approximately 5 \$ / m^2. This is due to the cost of the Bluetooth beacons. However the installation cost of RFID and Hybrid RFID-PDR is priced 2.8 \$ / m^2 and 0.3 \$ / m^2 approximately.

Tabelle 5.7: Cost of installation of the localization systems

Cost factor /Systems		Bluetooth	RFID	PDR	Hybrid BT-PDR	Hybrid RFID-PDR	Hybrid BT-RFID-PDR
	Cost of single landmark	74\$per Bluetooth beacon	0.3\$per RFID tag	Standalone	74\$per Bluetooth beacon, PDR :Standalone	0.3\$per RFID tag, PDR :Standalone	74\$per Bluetooth beacon, 0.3\$ per RFID tag, PDR :Standalone
Approximate cost of installation of the setup in US Dollars	Number of landmarks needed /m^2	0.063 Bluetooth beacons /m^2	9.4 RFID tags /m^2	Standalone	0.063 Bluetooth beacons /m^2, PDR : Standalone	1.1 RFID tags /m^2, PDR : Standalone	0.063 Bluetooth beacons /m^2, 1.1 RFID tags /m^2, PDR : Standalone
	Total cost /m^2	4.69\$/ m^2	2.82\$/ m^2	Standalone	4.69\$/ m^2	0.33\$/ m^2	5.02\$/ m^2
Approximate sensor cost in US Dollars		Freely available in today's Smart phone	RFID reader : 740 \$	3D compass : 177\$	Bluetooth : Freely available in today's Smart phone 3D compass : 177\$	RFID reader : 740 \$ 3D compass :177\$	Bluetooth : in Freely available in today's Smart phone, RFID reader 740 \$, 3D Compass : 177\$

The hardware cost of Hybrid BT - RFID - PDR sums up to approximately 879 \$. Since the density of the tags in Hybrid RFID - PDR is reduced, the cost of the setup is 0.33 \$ / m^2 approximately. However, RFID reader hardware remains as an expensive one that may cost up to 740 \$, but the price may decrease in near future. Although PDR remains to be a cost efficient system with the cost of the 3D compass about 177 \$, On the other hand, it fails to be reliable and accurate.

5.6.8 Flexibility

Bluetooth is quite flexible to adapt to a changing environment. This can be well achieved by rewriting the 3D location information to the node itself. Regarding a RFID system the installation process of RFID tags to the floor remains complex and time consuming. In the proposed scenario, when the environment is changed the location information for all tags has be reprogrammed which is quite cumbersome. Flexibility is not a confounding factor for 3D compass as it is a standalone solution. However, flexibility remains an affecting factor for Hybrid system when built with RFID.

5.6.9 Routing

Bluetooth can route the information in the built scatter net. The beacons in the environment can transfer information with each other. In case of RFID, the tags are passive and have no possibility of transferring information. Routing is not possible in PDR System without additional hardware. The Hybrid systems built with Bluetooth can perform routing.

5.7 Reconstruction of the Trajectory by the Localization Systems

The localization efficiency of the proposed systems is tested by walking over different predefined trajectories multiple times with different junctures as starting points. Figure 5.42 shows the reconstructed trajectory with the different localization system based on the measurement. It could be seen from the figure that the trajectory reconstructed by the Hybrid BT - RFID - PDR is closer to the real trajectory than the trajectories constructed with other localization systems.

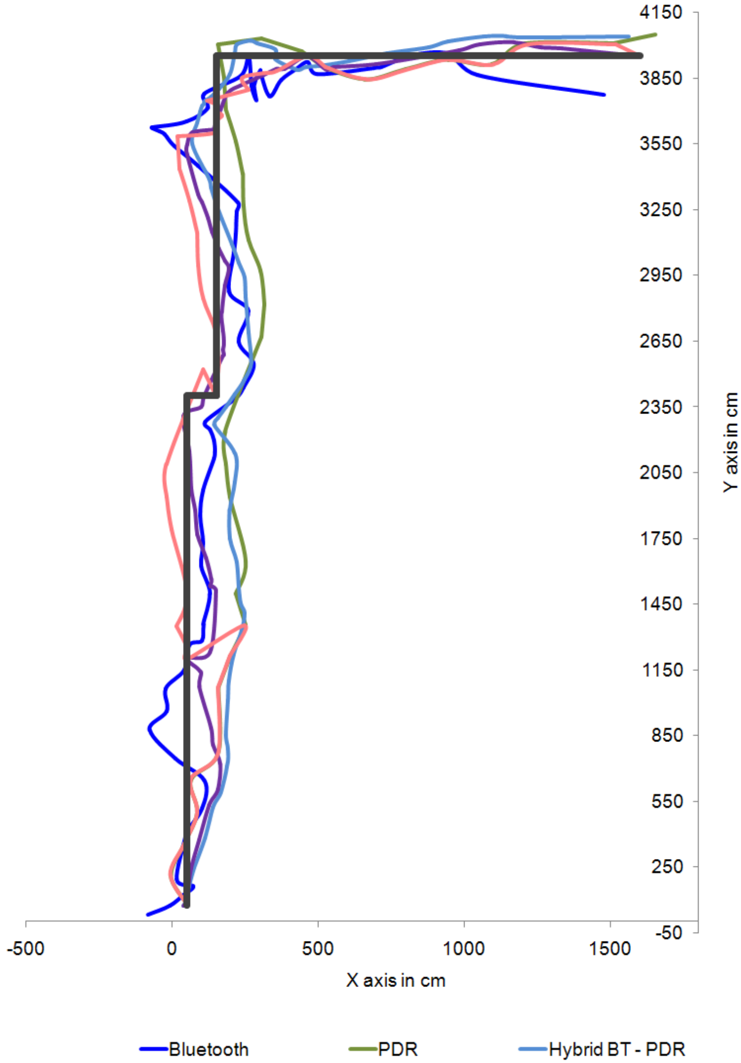

Abbildung 5.42: Reconstruction of the trajectory

5.8 Grading the Localization Systems

In order to elucidate an efficient localization system, in terms of vital criterion, the introduced localization systems are further graded based on their effectiveness.

It could be inferred from the table 5.8 that in terms of factor preciseness RFID remains a best pick, however RFID needs an additional hardware to route information and remains inflexible. The next best choice would be a Hybrid BT- RFID- PDR which is scalable, reliable, and convincingly flexible and can route information. It can be inferred from the table 5.8 that the Hybrid BT - RFID-PDR system scores to be the best for an efficient localization system.

Tabelle 5.8: Grading of localization systems

Factors /Systems	Bluetooth	RFID	PDR	Hybrid BT-PDR	Hybrid RFID-PDR	Hybrid BT-RFID-PDR
Accuracy	3m	21cm	2.5m	2.7m	2.5m	2m
Scalability	80%	100%	100%	100%	100%	100%
Robustness	Yes	Yes	Yes	Yes	Yes	Yes
Flexibility	Very good	Fair	Very good	Very good	Good	Good
Availability	No	No	Yes	Yes	Yes	Yes
Routing	Yes	No	No	Yes	No	Yes
Installation cost /m^2	4.69\$/m^2	2.82\$/m^2	Standalone	4.69\$/m^2	0.33\$/m^2	5.02\$/m^2
Performance	1.61s	1.626s	1.62s	1.66s	1.676s	1.676s

5.9 Navigation Results

Experiments are conducted in the three storey building to test the navigation ability of the system with respect to user guidance. The SVG map of the indoor building is shown in the figure 5.43. In this section, the results of the runtime navigation algorithm are presented followed by the screenshot of the navigated path over the SVG map.

5.9.1 Average Runtime of the Route Planning Algorithm

To evaluate the route planning algorithm, the metric runtime of the algorithm is employed. Runtime is defined as time taken to execute the algorithm from the submission of the request till the path is planned. Test runs are made with different localized position and different destination position to estimate the runtime of the

Abbildung 5.43: SVG map of the building

route planning algorithm. The runtime of the route planning algorithm (R_{tn}) is the summation of execution time of the procedures such as reasoner considering the user′s preference(R_{ru}) and route planning(R_{rp}). The runtime of the route planning algorithm is shown in the figure 5.44. The average runtime of the route planning algorithm is 365ms.

It is inferred from the figure results that the reasoner accounts for 15% of the total runtime and the rest 85% utilized as computation time to calculate the route. The navigation system is dynamic with a runtime efficiency of route planning algorithm as 365ms which is worth comparing to kSP algorithm [51] (that produces a runtime of 886ms when executed in the Smart phone with same number of nodes in the test environment).

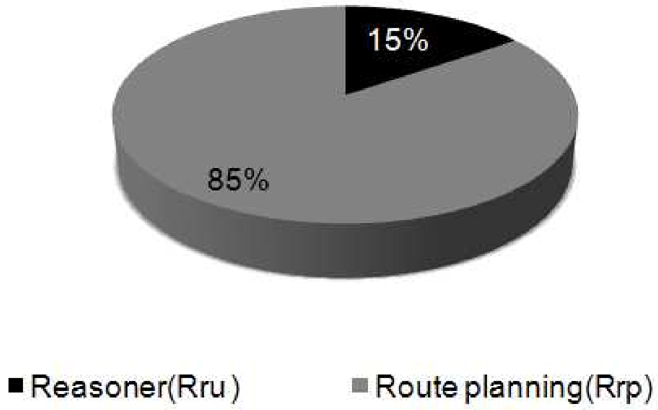

Abbildung 5.44: Average runtime of the route planning algorithm

5.9.2 Runtime of the Navigation Algorithm

The average runtime measurement of the different procedures in the navigation algorithm is depicted in the table 5.5. The algorithm is executed in a Nokia N95 Smart phone. When a new path had to be planned, the total time for the navigation algorithm would be the time taken for route planning plus the runtime of the reasoner and the localization algorithm. Hence the total time taken for navigation is 2142ms. The

Tabelle 5.9: Runtime of the navigation algorithm

	Localization	Reasoner	Route planning planning	Total time of the navigation algorithm
Time	1711ms	66ms	365ms	2142ms

navigation procedures run locally on the mobile phone and promise the privacy for the user. Moreover, the localization system is compact and could be integrated well in the smart phones.

5.9.3 Screenshot of the Navigated Path

Abbildung 5.45: Screen shot of the navigated path

Figure 5.45 shows the screenshot of the navigated path. The localized position is in the ground floor and the user opts to use the stairs thus removing the elevator nodes from the route calculation. The destination position is chosen to be in the second floor. The navigated path is the red path in the rendered SVG map. The users could choose to render his location on the navigated path.

6 Conclusion

Location based service has fascinated society in economic, commercial and scientific terms. Latest research shows that there is increase in demand of location based service. Location based services call for localization to determine the user's location, in order to provide him the desired information. The increased usage of Smart phones has influenced the increase in demand for location based service. Location based service finds application in almost all industries like healthcare, transportation, navigation, asset management etc. The challenge that prevail in the industry and the market is to find a global localization system that could be adapted for all location based services

In this thesis a prototype hardware design that could be integrated into the future's mobile phone and that enables automatic localization of the user is introduced. Novel systems and methods of localizing the user with augmented sensor technologies for indoor localization are designed and hybridization of sensors is established optimizing the solution satisfying the criteria for indoor localization. The results demonstrate the efficiency of each of the system in localizing the user from observations captured during real-world experiments. It has been generally demonstrated that the system is capable of constructing the path travelled by the user with agreeable accuracy and proposed navigation algorithm guides the user to its destination.

The proposed Bluetooth based localization system based on fingerprinting, though not able to provide uninterrupted service all the time, is able to provide an average accuracy of 3m. It is readily flexible, robust and able to route information to the central server and is available in almost all smart phones in the market today.

On the other hand the demonstrated RFID based localization system is very precise with an accuracy of 35cm and will be best choice for all applications where preciseness is the important criteria. The proposed coupled tag count and RSSI algorithm eliminates the false readings and makes the system reliable. Though not flexible, the system is robust, scalable and reliable at all instance. This system can be used for self localization where the user needs privacy and doesn't need his location to be tracked by others. The increasing demand for RFID based application will enable the future's Smart phone to equip with the RFID.

The standalone, cost efficient PDR system provides an average accuracy of 2.5m.

The presented peak declination algorithm reduces the number of false steps and thus the error accumulation of the system. The PDR system would be the best option for applications such as navigation where reliability is not a factor and coarse grained information is enough. However when combined with the augmented sensors PDR favours to be the best choice for location based service.

The Hybrid BT-PDR and Hybrid RFID-PDR are able to provide the accuracy of 2.5m and 2m respectively. However the trio combination Hybrid BT-RFID-PDR in an intelligent way makes the proposed system accurate, flexible, reliable, scalable, and robust and cost efficient with the ability to route information. The system is able to provide an accuracy of 1.5m on its average. The system satisfies the criteria for localization and would be a global system that could personalized for all location based services.

6.1 Suitable Applications for the Proposed Systems

The proposed Bluetooth system has a reliable coarse grained accuracy of approximately 3m and is able to provide fine grained accuracy of approximately 0.5m when large density of nodes is installed. Moreover, the system is able to route information. The only drawback of the Bluetooth system is providing the uninterrupted service all the time when scaled. Hence Bluetooth based localization system would be better choice for localizing user precisely within an area. For instance, localizing an object or person within a room, requesting location based information from the server, finding the nearest unused printer or computer in a laboratory.

Though the RFID localization opts to be the accurate localization system, the drawback of the system is the inflexibility of the installation of tags in the environment. However the availability of smart carpet with RFID tags may diminish the weakness. The other drawback of the proposed RFID is its short range. The system will not be able to detect the tag if it is above the range. RFID system would be the best choice for short range reading and where preciseness is the necessary factor. Some of the applications of RFID are information retrieval about the objects within museums (which doesn't require huge installation of tags and appropriate for the short range), navigation aid for visually impaired and locating people in emergency situation (where preciseness is the important factor), locating groceries in large supermarket or tracking persons or objects in large buildings (where the robustness and scalability is needed) and automatic registration of books in the library (which has be reliable).

Inertial sensors are the best option where cost is the important factor. Though the accuracy level of PDR system is coarse grained and error accumulates over time, it has the advantages as standalone and cost efficient system. Most of the navigation systems are built in combination with the inertial sensors. For instance, coarse grained location information is enough to navigate to the destination in indoor buildings. In such cases, inertial sensors are the best choice. Moreover almost all smart phones today are equipped with the inertial sensors hence user doesn't need a separate hardware installation.

Hybrid systems have many advantageous over the above proposed systems such as, they could operate in any environment, they can operate with or without the installation of sensor, they are comparatively cost efficient because it is built by reducing the density of sensor installed in the environment and are reasonably cost efficient compared to the single sensor based solutions like Bluetooth and RFID and more importantly they could satisfy the specified criteria for localization and be the efficient solution for all location based services. For instance, the Hybrid system will be suitable for all location based solutions such as resource management or tracking, locating or tracking peoples or objects, location based advertising, receiving alerts, asset recovery and so on.

6.2 Technical Contribution

The overall goal in this thesis was to design a system that could satisfy the criteria for localization efficiently and capable enough to guide the user in indoor environment. The strategic overview allows the proposed localization to be optimal and best choice for any localization based services. Below are the main technical contributions to this thesis

In Chapter 1 the criteria for efficient indoor localization that could be readily employed for any location based services are discussed.

The design of algorithms with proposed augmented sensors to locate and track the humans on the pedestrian path is subject of chapter 4. Novel methods for localizing the users with Bluetooth fingerprinting, RFID based coupled tag count and RSSI, Peak declination algorithm to detect the human movement are contributed.

These methods (when considered as independent modules) are particularly designed to be applied for specific application scenarios. However combining the sensors in different ways helps the system to be applicable for more application scenarios. In regard to this, novel methods of hybridization of sensors are presented (Chapter 4).

Moreover an optimized navigation algorithm with minimal runtime that guides the pedestrians in the indoor buildings to their destinations by integrating the localized information from any of the proposed localization approaches is presented in chapter 4.

Considering the agility of the system to be carried by the pedestrians, a prototype hardware setup that could be integrated into the smart phone is presented in this thesis (Chapter 5).

The suitability of the proposed systems for different applications is presented in chapter 6.

6.3 Results

The ideas in this thesis are experimented with the setup in the pedestrian path of an indoor building. The results of the characteristic and the localization performance of the system based on sensors and its hybridization are demonstrated with the application. Evaluation of all the proposed systems on the basis of criteria for localization to check the efficiency of the system to be adapted for location based service is presented. The localization results and runtime results of the navigation are compared with some of the state of art approaches. Moreover the proposed setup is compact enough to be used by the pedestrians.

Overall, based on these evaluation of the proposed systems one can judge the suitability of the proposed system for their location based applications.

6.4 Possible Future Work

In future research, the optimization of accuracy of the proposed approaches by training the system with the multipath fading effect from the metal doors obtained from local observations could be considered. Furthermore, the evaluation of the proposed systems in real scenarios (to guide patients in the hospital, locating things in the shopping mall) is to be judged. It would be particularly interesting to compare this approach with conventional guiding methods that are available in the market nowadays, to determine the impact of proposed system. Moreover the proposed navigation algorithm works visually and could be enhanced with the voice features to facilitate its usage for visually impaired peoples. One more future direction would be providing seamless outdoor- indoor navigation by combining the system with GPS technology.

The proposed interface can be extended further by additional sensors, such as temperature sensors, and cameras to increase the perquisite in supermarket for monitoring the diary products.

Integrating the location-specific data with a web based server and hence opening the system to resources available on the Internet, such as map data from Google Maps, and any other freely or commercially available location-specific data is also a work that could be considered. This direction has the primary goal to close the loop to interact with the World Wide Web.

Literaturverzeichnis

[1] *BTnode - http://www.btnode.ethz.ch/*.

[2] *CEAN A528 UHF rfid reader - http://www.caen.it/rfid/*.

[3] *Handheld RFID reader - http://www.tracient.com/handheld-rfid-readers.html/*.

[4] *Honeywell HMC 6343 - http://www.honeywell.com/*.

[5] *Nokia RFID reader - http://www.mobilemag.com/2004/03/16/nokia-5140-rfid-reader/*.

[6] *RFID EPC specification - http://www.epcglobalinc.org/home/*.

[7] ARULAMPALAM, M. S., S. MASKELL, N. GORDON und T. CLAPP: *A Tutorial on Particle Filters for On-line Nonlinear/Non-Gaussian Bayesian Tracking*. IEEE Transactions on Signal Processing, S. 174–188, February 2002.

[8] BAHL, P., , P. BAHL und V. N. PADMANABHAN: *RADAR: An In-Building RF-based User Location and Tracking System*. In: *IEEE Infocom 2000)*, S. 775–784, Tel-Aviv, Israel, March 2000.

[9] BANCROFT, J. B., G. LACHAPELLE, M. E. CANNON und M. G. PETOVELLO: *Twin IMU-HSGPS Integration for Pedestrian Navigation*. In: *Ion GNSS 2008*, Georgia,USA, 2008.

[10] BARGH, M. S. und R. DE GROOTE: *Indoor localization based on response rate of bluetooth inquiries*. In: *MELT '08: Proceedings of the first ACM international workshop on Mobile entity localization and tracking in GPS-less environments*, S. 49–54, New York, NY, USA, 2008. ACM.

[11] BRENER, N. E., S. S. IYENGAR, H. C. LOONEY, N. VAKAMUDI, D. YU, Q. HUANG und J. BARHEN: *Three-dimensional route planning for large grids*. Journal of Indian Institute of Sceince, 2004.

[12] CONNAIRE, C. O., K. FOGARTY, C. BRENNAN und N. O'CONNOR.: *User Localisation using Visual Sensing and RF Signal Strength*. In: *ImageSense 2008 - Workshop on Applications, Systems, and Algorithms for Image Sensing, at the 6th ACM Conference on Embedded Networked Sensor Systems*, 2008.

[13] CORRALES, J. A., F. A. C. HERÍAS und F. T. MEDINA: *Hybrid tracking of human operators using IMU/UWB data fusion by a Kalman filter*. In: *HRI*, S. 193–200, 2008.

[14] FELDMANN, S., K. KYAMAKYA, A. ZAPATER und Z. LUE: *An indoor Bluetooth-based positioning system: concept, Implementation and experimental evaluation*. In: *ICWN 2003*, Las Vegas, USA, June 2003.

[15] FISCHER, G., B. DIETRICH und F. WINKLER: *Bluetooth Indoor Localization System*. In: *1st Workshop on Positioning, Navigation and Communication 2004 (WPNC)*, Hannoversche Beitraege zur Nachrichtentechnik, S. 148. Shaker-Verlag, March 2004.

[16] GILLIÈRON, P.-Y., D. B¸CHEL, I. SPASSOV und B. MERMINOD: *Indoor Navigation Performance Analysis*. In: *Proceedings of the 8th European Navigation Conference GNSS*, 2004.

[17] GWON, Y., R. JAIN und T. KAWAHARA: *Robust indoor location estimation of stationary and mobile users*. In: *Proc. INFOCOM 2004. Twenty-third AnnualJoint Conference of the IEEE Computer and Communications Societies*, Bd. 2, S. 1032–1043, März 7–11, 2004.

[18] HIGHTOWER, J., C. VAKILI, G. BORRIELLO und R. WANT: *Design and Calibration of the SpotON Ad-Hoc Location Sensing System*. Techn. Ber., University of washington, 2001.

[19] ISTV·N NAGY, A. L. B.: *A Global Path Planning Algorithm, Based on Maximal Localization Error*. In: *Budapest Tech Jubilee Conference 2004*, Budapest, September 2004.

[20] JEVRING, M., R. DE GROOTE und C. HESSELMAN: *Dynamic optimization of Bluetooth networks for indoor localization*. In: *CSTST '08: Proceedings of the 5th international conference on Soft computing as transdisciplinary science and technology*, S. 663–668, New York, NY, USA, 2008. ACM.

[21] KLEINER, A.: *Mapping and Exploration for Search and Rescue with Humans and Mobile Robots*. Ph.D., University of Freiburg, 2008.

[22] KLEINER, A. und D. SUN: *Decentralized SLAM for pedestrians without direct communication*. In: *Proc. IEEE/RSJ International Conference on Intelligent Robots and Systems IROS 2007*, S. 1461–1466, 2007.

[23] KOTANEN, A., M. HANNIKAINEN, H. LEPPAKOSKI und T. D. HAMALAINEN: *Experiments on local positioning with Bluetooth*. In: *Proc. International*

Conference on Information Technology: Coding and Computing [Computers and Communications] ITCC 2003, S. 297–303, 2003.

[24] LADETTO, Q., B. MERMINOD, P. TERRIER und Y. SCHUTZ: *On Foot Navigation: When GPS Alone is Not Enough*. The Journal of Navigation, 53(02):279–285, 2000.

[25] LIKHACHEV, M., D. FERGUSON, G. GORDON, A. T. STENTZ und S. THRUN: *Anytime Dynamic A*: An Anytime, Replanning Algorithm*. In: *Proceedings of the International Conference on Automated Planning and Scheduling (ICAPS)*, June 2005.

[26] LIM, A. und K. ZHANG: *Advances in Applied Artificial Intelligence*, Bd. 4031/2006 d. Reihe *Lecture Notes in Computer Science*, Kap. A Robust RFID-Based Method for Precise Indoor Positioning, S. 1189–1199. Springer Berlin / Heidelberg, 2006.

[27] LIU, X., M. D. CORNER und P. J. SHENOY: *Ferret: RFID Localization for Pervasive Multimedia*. In: *Ubicomp*, S. 422–440, 2006.

[28] MAHTAB HOSSAIN, A. K. M., H. N. VAN, Y. JIN und W.-S. SOH: *Indoor Localization Using Multiple Wireless Technologies*. In: *Proc. IEEE Internatonal Conference on Mobile Adhoc and Sensor Systems MASS 2007*, S. 1–8, Okt. 8–11, 2007.

[29] MIYAKI, T., T. YAMASAKI und K. AIZAWA: *Multi-Sensor Fusion Tracking Using Visual Information and WI-Fl Location Estimation*. In: *Proc. First ACM/IEEE International Conference on Distributed Smart Cameras ICDSC '07*, S. 275–282, Sep. 25–28, 2007.

[30] NI, L. M., Y. LIU, Y. C. LAU und A. P. PATIL: *LANDMARC: indoor location sensing using active RFID*. In: *Proc. First IEEE International Conference on Pervasive Computing and Communications (PerCom 2003)*, S. 407–415, 2003.

[31] OJEDA, L. und J. BORENSTEIN: *Personal Dead-reckoning System for GPS-denied Environments*. In: *Proc. IEEE International Workshop on Safety, Security and Rescue Robotics SSRR 2007*, S. 1–6, 2007.

[32] PHILIPOSE, M., K. P. FISHKIN, D. FOX, D. HAHNEL, D. H‰HNEL und W. BURGARD: *Mapping and Localization with RFID Technology*. Techn. Ber., 2003.

[33] POPA, M., J. ANSARI, J. RIIHIJARVI und P. MAHONEN: *Combining Cricket System and Inertial Navigation for Indoor Human Tracking*. In: *Proc. IEEE*

Wireless Communications and Networking Conference WCNC 2008, S. 3063–3068, 2008.

[34] PRIYANTHA, N. B., A. CHAKRABORTY und H. BALAKRISHNAN: *The Cricket location-support system*. In: *MobiCom '00: Proceedings of the 6th annual international conference on Mobile computing and networking*, S. 32–43, New York, NY, USA, 2000. ACM.

[35] REKLEITIS, I.: *A Particle Filter Tutorial for Mobile Robot Localization*. Techn. Ber., Centre for Intelligent Machines, McGill University, Montreal, Quebec, Canada., 2004.

[36] RENAUDIN, V., O. YALAK und P. TOMÈ: *Hybridization of MEMS and Assisted GPS for Pedestrian Navigation*. Inside GNSS, January/February:34–42, 2007.

[37] RFID TAG INFRASTRUCTURES, S. DISTRIBUTED, J. BOHN und F. MATTERN: *Super-Distributed RFID Tag Infrastructures*, 2004.

[38] SCHINDLER, G., C. METZGER und T. STARNER: *2nd International Workshop on Location- and Context-Awareness(LoCA 2006)*, Bd. 3987/2006 d. Reihe *Lecture Notes in Computer Science*, Kap. A Wearable Interface for Topological Mapping and Localization in Indoor Environments, S. 64–73. Springer Berlin / Heidelberg, 2006.

[39] SCHNEEGANS, S., P. VORST und A. ZELL: *Using RFID Snapshots for Mobile Robot Self-Localization*. In: *Proceedings of the 3rd European Conference on Mobile Robots (ECMR 2007)*, S. 241–246, Freiburg, Germany, September 19-21 2007.

[40] SCHREINER, F. und H. ZIEMEK: *Mobility Aware Technologies and Applications*, Bd. 3744/2005 d. Reihe *Lecture Notes in Computer Science*, Kap. RAPOSI: Rapidly Installable Positioning System for Indoor Environments, S. 344–353. Springer Berlin / Heidelberg, 2005.

[41] SUBRAMANIAN, S. P., J. SOMMER, S. SCHMITT und W. ROSENSTIEL: *SBIL: Scalable Indoor Localization and Navigation Service*. In: *Proc. Third International Conference on Wireless Communication and Sensor Networks WCSN '07*, S. 27–30, 2007.

[42] SUBRAMANIAN, S. P., J. SOMMER, S. SCHMITT und W. ROSENSTIEL: *RIL : Reliable RFID based indoor localization for pedestrians*. In: *Proc. 16th International Conference on Software, Telecommunications and Computer Networks SoftCOM 2008*, S. 218–222, 2008.

[43] SUBRAMANIAN, S. P., J. SOMMER, S. SCHMITT und W. ROSENSTIEL: *INR : Indoor Navigator with RFID Locator*. Next Generation Mobile Applications, Services and Technologies, International Conference on, 0:176–181, 2009.

[44] SUBRAMANIAN, S. P., J. SOMMER, S. SCHMITT und W. ROSENSTIEL: *SHIL : Sensor Hybridization for Indoor Localization*. Submitted to INSS 2010, 2010.

[45] SUBRAMANIAN, S. P., J. SOMMER, F.-P. ZEH, S. SCHMITT und W. ROSENSTIEL: *PBIL : PDR for scalable Bluetooth Indoor Localization*. Next Generation Mobile Applications, Services and Technologies, International Conference on, 0:170–175, 2009.

[46] SUGANO, M., T. KAWAZOE, Y. OHTA und M. MURATA: *Indoor Localization System Using RSSI Measurement of Wireless Sensor Network Based on ZigBee Standard*. In: *The IASTED International Conference on Wireless Sensor Networks (WSN 2006)*, Banff ,Canada, July 2006.

[47] T. MAGEDANZ, F. SCHREINER, H. Z.: *GRIPS Generic Radio based Indoor Positioning System*. In: *2nd workshop on positioning, navigation and communication (WPNC 2005)*, Aachen,Germany, 2005. Hannoversche Beitr‰ge zur Nachrichtentechnik, Shaker Verlag.

[48] TANAKA, K.: *Multiscan-based map optimizer for RFID map-building with low-accuracy measurements*. In: *Proc. 19th International Conference on Pattern Recognition ICPR 2008*, S. 1–4, 2008.

[49] TANAKA, K., Y. KIMURO, K. YAMANO, M. HIRAYAMA, E. KONDO und M. MATSUMOTO: *A Supervised Learning Approach to Robot Localization Using a Short-Range RFID Sensor*. IEICE - Trans. Inf. Syst., E90-D(11):1762–1771, 2007.

[50] VARSHAVSKY, A., E. DE LARA, J. HIGHTOWER, A. LAMARCA und V. OTSASON: *GSM indoor localization*. Pervasive and Mobile Computing, 3(6):698 – 720, 2007. PerCom 2007.

[51] VASSILEIOS, T., A. CHRISTOS, K. PANAYOTIS und H. STATHES: *Semantically enriched navigation for indoor environments*. International Journal of Web and Grid Services, S. 453–478, December 2006.

[52] VLASSIS, N. A., N. M. SGOUROS, G. EFTHIVOULIDIS, G. PAPAKONSTANTINOU und P. TSANAKAS: *Global Path Planning for Autonomous Qualitative Navigation*. In: *Proc. 8th IEEE Int. Conf. on Tools with AI*, 1996.

[53] VORST, P., J. SOMMER, C. HOENE, P. SCHNEIDER, C. WEISS, T. SCHAI-

RER, W. ROSENSTIEL, A. ZELL und G. CARLE: *Indoor Positioning via Three Different RF Technologies*. In: *4th European Workshop on RFID Systems and Technologies (RFID SysTech 2008)*, Freiburg, Germany, June 10-11 2008.

[54] WANG, H., H. LENZ, A. SZABO, J. BAMBERGER und U. D. HANEBECK: *WLAN-Based Pedestrian Tracking Using Particle Filters and Low-Cost MEMS Sensors*. In: *Proc. 4th Workshop on Positioning, Navigation and Communication WPNC '07*, S. 1–7, 2007.

[55] WANT, R., A. HOPPER, V. FALC AO und J. GIBBONS: *The active badge location system*. ACM Trans. Inf. Syst., 10(1):91–102, 1992.

[56] WENDLANDT, K., M. BERHIG und P. ROBERTSON: *Indoor localization with probability density functions based on Bluetooth*. In: *Proc. IEEE 16th International Symposium on Personal, Indoor and Mobile Radio Communications PIMRC 2005*, Bd. 3, S. 2040–2044 Vol. 3, 2005.

[57] WENDLANDT, K., P. ROBERTSON, M. KHIDER, M. ANGERMANN und K. SUKCHAYA: *Demonstration of a Realtime Active-Tag RFID, Java Based Indoor Localization System using Particle Filtering*. In: *UbiComp 2007*, S. 108–111, 2007.

[58] WILSON, P., D. PRASHANTH und H. AGHAJAN: *Utilizing RFID Signaling Scheme for Localization of Stationary Objects and Speed Estimation of Mobile Objects*. In: *Proc. IEEE International Conference on RFID*, S. 94–99, 2007.

[59] WU, H., A. MARSHALL und W. YU: *Path Planning and Following Algorithms in an Indoor Navigation Model for Visually Impaired*. Internet Monitoring and Protection, International Conference on, 0:38, 2007.

[60] ZHOU, S. und J. K. POLLARD: *Position measurement using Bluetooth*. IEEE Journal on Consumer Electronics, 52(2):555–558, 2006.