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Wireless industrial indoor localization and its application

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A complete, structural and comprehensive description of indoor localization technology is presented in this paper. It concluded the basic techniques for distance measurement in indoor localization, the basic localize principles, the topologies and algorithms which are often used in indoor localization area. Then how to perform indoor localization with sensors which are available in modern smartphones are detailly discussed. A topic about how to design an indoor localization based on the previous concluded knowledge is introduced and an example was given. In the end, the value of indoor localization for industry is briefly talked.

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Acronyms

LBS	Location-based service
GNSS	Global navigation satellite system
GPS	Global positioning system
UWB	ultra-width band
RFID	Radio-frequency identification
TOA	Time of arrival
TDOA	Time difference of arrival
RSS	Received signal strength
RSSI	Received signal strength index
FCC	Federal communication commission
DoD	Department of Defense
UiT	Norges arktiske universitet (University i Tromsø)
LNA	Low Noise Amplifier
RF	Radio frequency
VLC	Visible light communication
DSSS	direct sequence spread-spectrum
RTOF	Received time of flight
2-D	Two dimensions
3-D	Three dimensions
LOS	line of sight
MLE	Maximum likelihood estimation
PDR	pedestrian dead reckoning
IR	Infrared
SLAM	simultaneous localization and mapping

GP	Gaussian Process
k-NN	k-nearest neighbor
ITU	international telecommunication union
AP	Access point
UTD	Uniform Theory of Diffraction
ED	external device
GPR	Gaussian Process Regression
EKF	Extended Kalman Filter
UKF	Unscented Kalman filter
GS-KF	Gaussian sum Kalman Filter
PF	Particle filter
PD	photodiode
BLE	Bluetooth low energy
IoT	internet of thing
HAIP	High Accuracy Indoor Positioning
SRA	Server-Side Running Average
SKF	Server-Side Kalman Filter
KFPF	Kalman Filter-Particle Filter
MUSIC	multiple signal classification
MDI	motion dynamic information
BMI	building map information
SCS	smartphone coordinate system
FFT	fast Fourier transform
HPET	High Precision Event Timer
NTP	Network Time Protocol

NDK	Native Development Kit
ABS	Acoustic Background Spectrum
VAD	Voice Activity Detection
MM	magnetic matching
ULP	User Location Preference
ICT	Communication Technology
SMEs	Small and Medium Enterprises
DTW	dynamic time warping
LCSS	longest common subsequence
ANN	neural network

1 Introduction

1.1 indoor localization

To locate is one of the basic need of living life since the very beginning of this world while they need to find their targets. In the beginning, position information of targets is estimated by smelling, sounding, tracing and seeing.

As the world is developing, everything is becoming increasingly complicated, so does the space where we live in. Modern people are now dealing with a place with too much information. It is important for them to get as much as possible details about the environment around and the position of themselves.

In recent centuries, internet and mobile devices become so popular that almost no one can live without them. Together with billions of programs available in the world, Internet and computing devices are making life more convenient and world a better place. In the beginning of computer technology, computers are like calculators which needed operators to input all the information and made all the choices for them, results came with a long-term procedure. Computer science engineers work hard for decades to make them more intelligent, one of the features is the conception of “context awareness”[1], which can do some guess for users based on the historical and present information. Among these information, there is one called location. it contains three main factors: position, time, and objects (who or what). Therefor location information has a profound meaning. By the help of location information, we can not only supply services according to where you are, but also according to who you are and when you require the services. These services are called location based services(LBSs)[2].

A location-based service is a software-level service that uses location data to control features. As such LBS is an information service and has a number of uses in social networking today as information, in entertainment or security, which is accessible with mobile devices through the mobile network and which uses information on the geographical position of the mobile device.

1.2 project motivation

Currently most localization service are approached by the technology called Global navigation satellite system (GNSS). The most famous example of GNSS is the global positioning system(GPS), which was made to serve the need of military purpose in the beginning[3]. Now it is playing a vital rule in LBSs[4]. It is truly a success in many areas. However, GPS technology has its own limitation[5], which is that it can only get accurate position when the receiver is outside without any block of the signal.

However, most of the human activities are done in an inside environment[6], therefor indoor localization became an important subject as an implement of GPS. For so many years, pioneers are dedicated to find the best solutions. Thousands of articles can be found. Most researchers are focused on wireless signal approach in which use wireless signals for calculation of the position of target. Currently, there are lots of wireless standards that are studied. For example, Wi-Fi[7][8], Bluetooth[9][10], ultra-width band(UWB)[11], radio-frequency identification (RFID)[12] and so on.

Although tons of surveys or articles introduced different work or approaches of current achievement, there is no one article available gives a systematical and structural view of this area. That adds the challenges for companies which want to get inside this business or students who would like to do their researches inside this topic. When a reader read some work related to indoor localization, they feel like stepped into a huge city without map. This article would like to build the first map for future scholars and engineers. Though maybe not perfectly detail and complete due to the limit capability of the author. But everything has its first version. The author hopes this work can be improved in the future and fulfill its value by guiding more people into this area.

1.3 contributions of this work

So, the first contribution is that this is the first article which gives a comprehensive textbook-like introduction of indoor localization technology. This part of work can be seen in chapter 3. It abstractly concluded a systematical structure of indoor localization technological knowledge. As industrial engineer says:" see the big picture". After reading this part, it shall help the reader to be aware of what kind of knowledge they are reading about in the future study. Is it using basic TOA, TDOA, or RSS technology to measure? Is it using trilateration, scene analysis or proximity to determine the position? Is it device based or device free system… In the end of chapter 3, a survey of those algorithms which are used to improve indoor localization systems so that they can get better performances. The first value of this part is helping people to understand future articles easily. The second value of this part is helping readers to make decisions when they plan to build an indoor localization system. Which approaches shall they choose.

The second contribution of this work is a complete analyzing of smart phone based indoor localization. There are lots of work which introduce smart phone based indoor localization. However, none of them completely talked about all available approaches. There are some articles talked about hybrid indoor localization system combing motion sensors and Wi-Fi or Bluetooth[13]. WAIPO[14] utilized Wi-Fi, camera, magnetic sensor. [15] combined Wi-Fi, Bluetooth, LTE and magnetic sensor. But they ignored the fact that the modern smart telephones are equipped with light sensor, camera, microphone, motion sensor, magnetic sensor except Bluetooth, Wi-Fi and GSM. In chapter 4, there will be a complete introduction of modern smartphone based indoor localization. By complete, it does not only mean all the sensors are introduced, it also means all the possible approaches of each sensor will be also described. In the end of this chapter, some fusion approaches of these sensors are introduced.

The third contribution of this work is trying to propose a procedure and flow of how to design an indoor localization system. The most of those research articles follow this pattern: xxx based localization is good, related work are not good enough, the author made his own contribution by his proposal, experiment test and conclusion. However, no one thinks in a real-life project way, which is when you are asked to build an indoor localization based on some kinds of need, how to build or how to choose. With the help of part 3 and part 4, this article will show the way how those knowledges can be used as a reference for designing the indoor localization system with the example of the authors' current university campus in Narvik, Norway.

The remainder of this article is arranged in this way: Chapter 3 gives structural description of indoor localization technology knowledges. Chapter 4 focus on smartphone based indoor localization. Chapter 5 talks about indoor localization system design. Chapter 6 talks about indoor localization for industrial applications. Chapter 7 talks about future work and Chapter 8 gives conclusion of this work.

2.Location based service

2.1 Context awareness

2.1.1 what is context awareness-based service

One of the reasons why Location based service is so important is because it plays a vital role in context awareness services. In the beginning of computer usages, it was a tool which needed operators to interact with computer devices by frequently inputting all the information that is needed for calculations. Intention of operator can't be predicted by the machine[16]. In 1994, Bill N. Schilit and Marvin M. Theimer [17] introduced context as location, identities of nearby people and objects, and changes to those objects. Context-aware was to sense the "context" defined before.

Nowadays, the common accepted definition of context-aware is from [1]: "A system is context-aware if it uses context to provide relevant information and/or services to the user, where relevancy depends on the user's task."

2.1.2 how context awareness-based service works

According to the definition we introduced before, there can be four steps in context-awareness service:

1) Understand the user: This refers the information collecting and analyzing of the user in order to get the data of who the user is and his habits or behavior pattern. This indicates what the user would like to have in a certain context.
2) Understand the service available: This is the survey of services which are available in certain locations during specific periods of time. It is a resource gathering and service understanding.
3) Match the service with the user's task: This is the stage when the context-aware service gives its value by offering the relevant information or service to the user.
4) Update the user's context: The system can update itself so that it can offer more accurate service and information.

All these steps are performed now on our personal smart devices such as smartphones, wearable device or medical monitoring devices. And due to the fast development in embedded system and mobile phones, context-awareness services have gotten a huge playground to show their values by improving the daily life experience and have a profound influence on human activities every day and everywhere.

2.1.3 location-based service and context awareness-based service

Among the data context-awareness service takes in account, location information is no doubt one of the most important one. The location the user always is during working time indicates user's occupation. Information about where is user on eating time, if user go to some gym and how often, where user travels and how often, which flight, what kind of hotel and so on indicates user's lifestyle and preferable.

2.2 Location-based services (LBSs)

2.2.1 what is LBSs

LBSs starts from the conception of location. Location information is one of the most important details in our daily life. According to [18], location can be divided into virtual location and physical location.

The physical location can be further divided into “descriptive locations”, “spatial locations” and “network locations”. In this article, the term location refers to “spatial locations”, which means a single point in the Euclidean space and position in a two- or three- dimensional coordinates.

So LBSs roughly means offering service to the users based on the user’s spatial locations. In [19], LBSs were defined as “services that depend on and are enhanced by the positional information of the mobile device”. Therefor Location based services are those services which are centered on users’ locations and environments, currently or historically and it is based on mobile devices. For example, mapping, navigation, social networking, property tracking and so on. It is with the user for the whole day from morning to evening. People can find specific services around and navigate to desired destination. Location based service can help us to find keys, cars, shops and even friends around by continuously sharing and searching the current locations.

It is a software-level service that take location data into consideration to control features. As such LBS is an information service and has number of uses in social networking today as information, in entertainment or security, which is accessible with mobile devices through the mobile network and which uses information on the geographical position of the mobile device.

Location-based services (LBSs) have been evolving in a rapid speed due to that they are playing an importance role and giving users increasing better experience[20]. The growth of LBS industry is soaring. According to a report from Berg insight Global[21], in North America, LBS revenues are forecasted to grow from almost US$ 1.8 billion in 2013 to nearly US$ 3.8 billion by 2018.

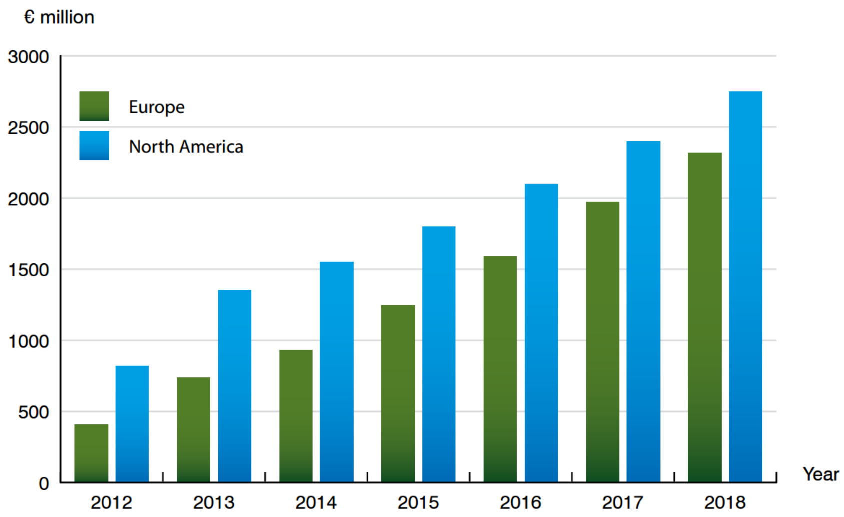

Figure 1 - Mobile LBS revenue forecast, € million (2012–2018)[21]

2.2.2 development of LBSs

The first popularization of LBSs may derive to 1996[22]. In 1996 America federal communication commission (FCC) formally issued a rule that quires all US mobile operators to locate emergency callers (E-911). At that time, there was around 50% 911 are dialed by mobile telephones and the callers sometimes can’t offer their location information. And this percentage was growing, in order to solve emergency problems quicker and more accurately. E-911 required mobile services suppliers to achieve localization services with an accuracy within 125 m before the first of October in 2001. And the confidence interval of this localization result had to be greater than 67%. And after that, FCC was keeping giving higher and higher requirement, thus pushed the development of LBSs from mobile service suppliers.

In Europe, a similar rule was issued in 2000 and it is called E-112. After that many countries such as Japan and South-Korea also made this kind of rules to push the development of LBSs in their own territory. LBSs became a global famous conception since then. And there came the spring of it, it is growing in a rapid speed.

2.3 Global navigation satellite system (GNSS)

GNSS indicates systems that give time and position information in a world-wide range. A whole system contains satellites, ground monitor systems and user's devices. It can offer real-time, precise time and location information of objects which are on the earth surface or close to the surface. currently, there are three GNSS service supplier: American GPS, Russian Glonass and Chinese BeiDou Navigation Satellite System.

As time goes, GNSS systems play an increasing important role in areas such as ocean exploration, telecommunication, weather analyzing, oil and gas exploration, traffic navigation and so on. It will influence our lives in different aspects. GNSS system now is one of the three information technology industries. It has an unreplaceable meaning on economy, military and political activities.

2.4 GPS

GPS was firstly introduced by United States Navy as an experiment to track US submarines which are carrying nuclear missiles. In the beginning, there were six satellites orbiting the poles, submarines observed the satellite changes in Doppler and then calculated their own location. In the early 1970's, the Department of Defense (DoD) decided to use satellites to build a robust, stable navigation system. The first timing and ranging satellite was launched in 1978. Until 1993, a fully operable GPS system with 24 satellites system was completed. Today, GPS is a multi-use, space-based radio navigation system owned by the US Government. And it plays an extremely important role all around the world in navigation, aviation, surveying, mapping and geophysics, telecommunication and so on. People can hardly image life without GPS[3]. Owing to the latest technological advances, GPS receivers are able to locate themselves with an error of 5 meters outdoors[5].

2.5 From outdoor to indoor

Statics from America strategy analyze tells that human beings spend around 80% ~ 90% of their time indoor. And 70%~ 80% of those most important communication activities are done under indoor situation[6][23]. According to [24], there are around 2.32 billion smartphone users in 2017. And this number is still increasing. This means there is a huge potential in indoor localization market.

Although GNSS has huge advantages in localization activities, it can be hardly used in indoor localization. Normally there is a 20-30 dBm when there is blocks such roofs[25]. This poor performance makes it hardly possible to work in indoor occasions.

GNSS system, for example GPS, can achieve an accuracy of around 5 meters, which is fair enough in outdoor applications. However, it does not work in an indoor situation where 5 meters can mean a different room or unit. In [26]the author made an argument that suppose the GPS can have a same good performance as outdoor situation. The 5-meters error may mislead the program to think object is in a totally different another shop, and to offer a totally wrong LBSs notification and service. This mistake gives users unpleased experience instead of convenience. This is not what LBSs aim to.

Therefor there must be an implement way to get location and time information under the roof with a better accuracy performance.

There are some researchers proposed ways to help GPS working inside buildings. For example, Kerem[5] proposed to use repeaters in indoor environment. They consist of a directional antenna for receiving a non-overlapping set of GPS satellites, a LNA (Low Noise Amplifier), a power amplifier for compensating the antenna and cable losses, and a transmitting antenna for re-radiating the amplified GPS signals.

Paul[23] analyzed a technology called assisted GPS (A-GPS) which was intended to give GPS a better performance in indoor applications, it still can’t meet our requirement. According to the study conducted in [23], it can just ensure an accuracy within 100 meters. This is impossible for most of the indoor location cases.

3 Basics of indoor localization

In one of the newest survey about indoor localization [27], the author claimed that it contains all the indoor localization research area and gave comprehensive schemes. They made a whole diagram of comparison to prove that.

Technology or feature	Liu	Gu	Mautz	Deak	Koyuncu	Ours
Infrared mobile reader	No	Yes	No	No	No	Yes
Infrared badge	Mention	Yes	Yes	Yes	Yes	Yes
Laser (passive)	No	No	Yes	No	No	No
Ultrasound passive	No	Yes	Yes	No	Yes	Yes
Ultrasound active	Mention	Yes	Yes	Yes	Yes	Yes
Audible sound active	No	Yes	Yes	No	No	Yes
Audible sound passive	No	No	No	No	No	Yes
Audible sound ambient	No	No	No	No	No	Yes
Magnetic generated	No	Yes	Yes	No	No	Yes
Magnetic ambient	No	No	Yes	No	No	Yes
RFID mobile tag	Yes	Yes	Yes	Yes	Yes	Yes
RFID mobile reader	No	No	Yes	No	No	No
Wi-Fi	Yes	Yes	Yes	Yes	Yes	Yes
Bluetooth	Yes	Yes	Yes	Yes	No	Yes
ZigBee	No	No	Yes	No	No	Yes
UWB	Yes	Yes	Yes	Yes	Yes	Yes
Tomographic (water resonance)	No	No	No	Yes	No	No
Cameras infrastructure	Mention	Yes	Yes	Yes	Yes	Yes
Cameras (portable)	No	No	Yes	No	No	Yes
Floor tiles	No	No	Yes	Yes	No	No
Air pressure	No	No	Yes	Yes	No	No
Inertial	No	No	Yes	Mention	Yes	Yes
Ambient light	No	No	No	No	No	Yes
Artificial light (no encoding)	No	No	No	No	No	Yes
Artificial light (encoded)	No	No	Yes	No	No	Yes
Indoor AGPS, pseudolites	Yes	No	Yes	No	Yes	Yes
Cellular	Yes	No	Yes	Mention	Yes	Yes
TV, FM	No	No	Yes	Yes	No	Yes
Classification-guided	Partial	Partial	No	Yes	Partial	Yes

Figure 2 - Previous surveys comparison from [26]

However, the survey is not complete and is not comprehensive enough. For example, those approaches based on the motion sensor[28] which is built in smart telephones, they ignored the fact there are approaches which are "device-free"[29]. The authors claimed they gave comprehensive schemes. Although they introduced AOA, TOA, RSS-based, fingerprinting approaches and then RF platforms such as Bluetooth, Wi-Fi, Visible Light Communication, sound-based Technologies and others are described. However, they ignored the fact that fingerprinting has to use the knowledge of RSS or AOA or TOA, and these three are basics for other approaches such as Bluetooth, Wi-Fi or VLC. They are hardware independent. Fingerprinting can be also used for a lot of other approaches. Most of the surveys available in the database can't give a structural or systematical view of these techniques.

This chapter tries to introduce indoor localization with a comprehensive structure and levels. In 3.1, it will introduce those basic approaches such as TOA, TDOA, AOA, RSS-based techniques. These techniques are talked very often when it comes to indoor localization. Actually, AOA, TOA can also be used for outdoor localization applications. They are the basic way to measure distances with the help of signals.

In 3.2 the basic principles will be introduced. There are distance-based approaches despite how the distances are achieved, angel-based despite how the angles are achieved, scene analyzing based on fingerprinting despite what kind of finger or signature and approximate which just try to ensure the target is in some defined space unit despite what method are used.

In order to achieve indoor localization, most researchers would require the target to carry some devices. The system locates the devices instead of human. they are called device-based approaches. The study of [27] are put under the device-based category. However, there are researchers working on device-free indoor localization systems which does not require the target to carry any devices.

In the device-based scheme, the best device is our smart telephone which people like to take with all the time. So instead of talk about those massive researches. This article would like to narrow the study area into smart telephone based indoor localization and in the future how this can be used in industry area.

In the last of this part, after all the categories are introduced. There is one special detail will be talked. That is the topologies of the system. This is a must-think and always-ignore problem that we have to consider when design a indoor localization system.

3.1 Basic distance detecting techniques.

3.1.1Time of arrival(TOA)

As we all know, if the speed of travelling can be mathematically described, then the distance can be calculated as

$$D = \int_0^{TOA} speed(t)dt \tag{1}$$

Where $speed(t)$ represent the instantaneous velocity at time dt. In this application,

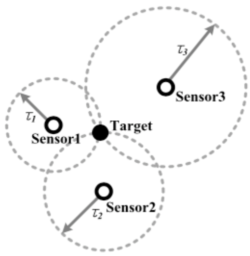

Figure 3 – TOA at three positions[30]

$speed(t)$ is the propagation time of radio signal through the measured space. As is shown in Figure 3, the distances between sensors and the target can be determined when TOA are measured. Then the joint point of circles determined by sensors and distances is the position of the measured target. In order to get a determined single joint point, there must be at least 3 circles, which indicates at least 3 sensors are needed in a 2-D positioning system.

In general, direct TOA results in two problems. First, as the RF signals travels in the space with a speed close to light, therefore a slice error in the measurement of the TOA can lead to a huge error in localization result, there must be extremely precise, high speed timer and clean code (execution time of the program code can't be ignored in this kind of situation.) for the measurement device. All transmitters and receivers in the system have to be precisely synchronized. Second, a timestamp must be labelled in the transmitting signal in order for the measuring unit to discern the distance the signal has travelled. TOA can be measured using different signaling techniques such as direct sequence spread-spectrum (DSSS) [31] or ultra-wide band (UWB) measurements [11].

3.1.2 TDOA

As we discussed before, TOA has high requirement of hardware and software on not only sensors but also mobile devices. It is not practical for our telephones. So in order to eliminate the requirement of mobile device, an improved method called TDOA was developed.

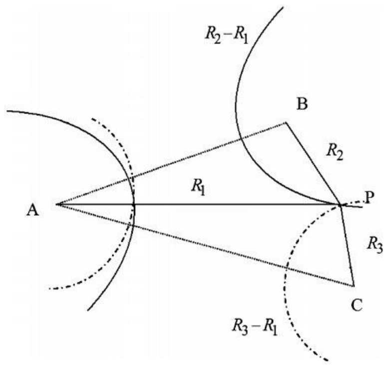

Figure 4- Positioning based on time difference of arrival (TDOA)[32].

Instead of measuring the TOA on different sensors, the difference between arrival time will be used to determine the relative position of the signal transmitter, which is our mobile devices. For example, if sensor 1, sensor 2 and sensor 3 receive a signal at t1, t2 and t3 respectively. Due to the fact at we do not know when exactly the signal was sent, we can know the |t2 – t1|, |t3 – t1| and |t2 – t3|

At the same time the distance differences between sensors are determined by[33]

$$R_{i,j} = \sqrt{(x_i - x)^2 + (y_i - y)^2 + (z_i - z)^2} - \sqrt{(x_j - x)^2 + (y_j - y)^2 + (z_j - z)^2} \tag{2}$$

where (x_i , y_i , z_i) and (x_j , y_j , z_j) represent the fixed receivers i and j; and (x, y, z) represent the coordinate of the target[33][34].

$$R_{i,j} = \int_0^{|t_i - t_j|} speed(t)dt \tag{3}$$

So there will be three equations

$$\begin{cases} \int_0^{|t_1-t_2|} speed(t)dt = \left| \sqrt{(x_1-x)^2+(y_1-y)^2+(z_1-z)^2} - \sqrt{(x_2-x)^2+(y_2-y)^2+(z_2-z)^2} \right| \\ \int_0^{|t_3-t_2|} speed(t)dt = \left| \sqrt{(x_3-x)^2+(y_3-y)^2+(z_3-z)^2} - \sqrt{(x_2-x)^2+(y_2-y)^2+(z_2-z)^2} \right| \\ \int_0^{|t_1-t_3|} speed(t)dt = \left| \sqrt{(x_1-x)^2+(y_1-y)^2+(z_1-z)^2} - \sqrt{(x_3-x)^2+(y_3-y)^2+(z_3-z)^2} \right| \end{cases} \quad (4)$$

and the unknown values of x, y, z are determined. Thus we can determine the position of target.

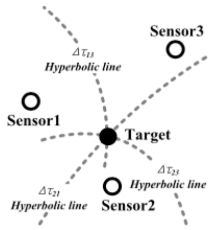

Figure 5- determine the target by hyperbolics from sensors [30]

In a short way, the TDOA method uses the time differences among the signals received by multiple sensors for localization. Plotting the time differences obtained from two sensors allows to draw a hyperbolic line, and another hyperbolic line is formed by another sensor. The target position is then recognized using the intercepts of the two hyperbolic lines.

The TDOA method is advantageous over the TOA method in that it does not need a target sensor synchronization because only sensors should be synchronized. However, synchronization among sensors which also could be a burden for hardware implementation if the sensors are sparsely spaced in a big area and if the target is located out of the internal boundary of the polygon which each sensor forms the localization error increases.

3.1.3 Received time of flight (RTOF)

As discussed before, TOA and TDOA need the sensors to be synchronized, thus makes them hard to be deployed in real life. Therefore, they came a solution to eliminate this requirement called received time of flight.

In this method, the signals sent by the target travel to sensors. Instead of measuring the time or distance on the sensors. They simply send back these signals to the target. When the target gets the responses, it knows how long time it takes for signals to go to sensors by dividing the time by 2. Thus it knows the distance and position of itself by the same way as TOA.

In some cases such as huge space and the target is a special device equipped with fast speed and precise timer and programmed to response timer and input interrupt in an extremely efficient way, this is a great solution. However, in real life the most targets are devices with an operate system inside, the delay of response is unpredictable and uncontrollable.

3.1.4 Angle of arrival (AOA Estimation):

Different from the previous three methods, AOA try to figure out the distance in a geographic way. This will of course solve the problem of timer and response delay.

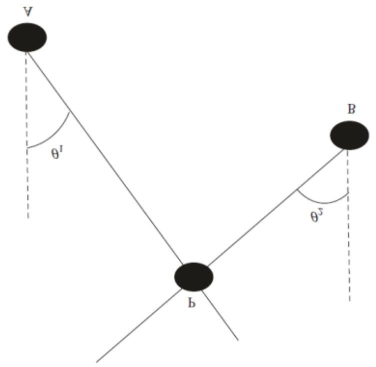

Figure 6 - Positioning based on AOA measurement[27].

In this method, the receivers are equipped with angle sensors which can measure the angles of where the signals come from. After the receivers sending these angles to the sever, the server can draw lines from these receivers and the intersection is the relative position of the target. As shown in Figure 6, in 2-D positioning system the position can be determined by at least two receivers. This is better than the previous methods which require at least 3 receivers.

However, despite the requirement of the antennas of the hardware. Targets' movement effects the results of the measurement. The accuracy is limited by the shadowing, by multipath reflections arriving from misleading directions, or by the directivity of the measuring aperture[35].

3.1.5 Received Signal Strength (RSS)

The previous discussed techniques are based on one condition which is line of sight (LOS) which indicates that the signal can directly go from transmitter to the receiver. However, this condition is hard to be meet due the complex indoor environment. An alternative is to measure the strength of the received signal and calculate the distance base on the signal propagation model[36]:

$$P(R) = P(R_0) - 10n * \log(\frac{R}{R_0}) - \begin{cases} nW \times WAF (nW \prec C) \\ C \times WAF \,(nW \geq C) \end{cases} \tag{5}$$

where R represents the distance between the transmitter and the receiver, R0 is a reference distance, p(R) and p(R0) the signal strength received at R and R0 respectively, nW represents the number of obstacles (walls) between the transmitter and the receiver, WAF means the wall attenuation factor, C is the maximum number of obstacles between the transmitter and the receiver, and n is the routing attenuation factor which could be determined by both theoretical and empirical calculations[36].

This equation (5) can be simplified to path loss model as:

$$PL = PL_0 + 10\gamma \log_{10} \frac{d}{d_0} + \Delta \tag{6}$$

where PL is total path loss at distance d, PL_0 is total path loss at a distance d_0, γ is path loss exponent and Δ is variable accounting for variation of the mean and is often referred to as shadow fading[37].

RSS value is now can be read in both mobile devices and routers despite Bluetooth platform or Wi-Fi platform. Therefore, it one of the most popular tool for indoor localization. Apple's iBeacon system, which is currently the only commercialized system is also based on this method.

There are two ways to utilized RSSI based technique. They are pass loss model based localization and fingerprinting based localization. The former one try to calculate the distance according to equation (6) [37]while the later one try to build a signal map and estimate the position by matching the current measured RSSI the RSSI value stored in the signal map[38][39][40].

3.2 Positioning Principle

In [41] the author introduced four principles used in building positioning systems. They are Trilateration, Triangulation, Scene Analysis and Proximity. These principles used can provide a fast calculation of the position. It can also provide a good accuracy depending on the system architecture too[42]. In this paper, trajectory principle is added to be fifth one due to that pedestrian dead reckoning becomes one of the hot topics in indoor localization area.

3.2.1 Trilateration

As illustrated in Figure 7, the trilateration based positioning algorithm uses three fixed non-collinear reference nodes to calculate the physical position of a target node (in 2-D).

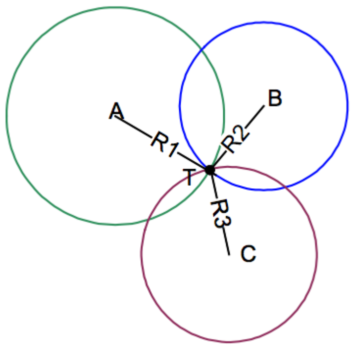

Figure 7 - trilateration[42]

Based on the coordinates of three reference nodes: $A(x_1, y_1), B(x_2, y_2), C(x_3, y_3)$, and the corresponding distances from each reference node to the target node: R_1, R_2, R_3, we can obtain the following equations:

$$\begin{cases} (x_1 - x)^2 + (y_1 - y)^2 = R_1^2 \\ (x_2 - x)^2 + (y_2 - y)^2 = R_2^2 \\ (x_3 - x)^2 + (y_3 - y)^2 = R_3^2 \end{cases} \tag{7}$$

where (x, y) denotes the (unknown) coordinates of the target T.

TOA, TODA and ROTF belong to this category.

3.2.2 Triangulation

When AOA measurements are available, position of target can be calculated. In this approach, angles can be measured instead of distances. Since the distance between nodes are known in most situations, there just need two angles to figure out the position. Therefor just 2 nodes are enough. As shown in Figure 8, where A and B represent reference nodes, after obtaining the angles θ_1 , and θ_2 , the physical position of T (representing the target to be located) could then be calculated based on the predetermined coordinates of the reference nodes.

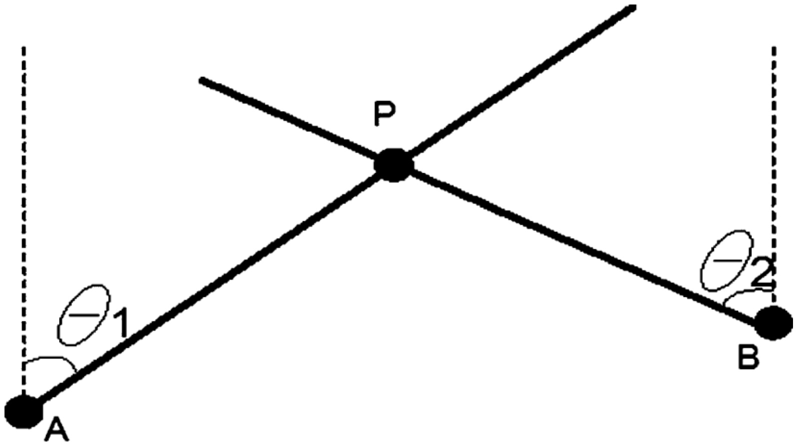

Figure 8 - Triangulation[34]

3.2.3 Scene Analysis

Scene Analysis is another principle of positioning in which special information is collected in specific position and this position of target can be decided when it get the same special information. The most approach uses scene analysis is fingerprinting. A fingerprint is the signature that differentiates the scene from other ones [43]. It is the unique feature or a few features of the location. It works by building a feature map of the location and stored in the databased. When the target reached a location and the new collected feature matches a stored feature in the data based, a location will be matched.

3.2.4 The proximity

In lots of cases, the requirement of the system is not to know the exact spatial location, it need to identify the target in a known set of zones, for example, room, section, or within 5-meters around. In [44], the author developed an API meant to support applications for which the exact position of a mobile terminal is not a primary requirement, but it suffices to identify a proximate zone. It is mainly used in Radio Frequency based systems. For example, apple's iBeacon[45] can be considered as one of this. Actually, fingerprinting can be also regarded as a proximity approach with a finer accuracy. It can be said that most scene analysis is some kind of proximity,[46] used acoustic sound information in some special places as basis for indoor localization. One of the popular ways to achieve proximity is Maximum likelihood estimation (MLE).

3.2.5 Trajectory

Different from the previous ones, this principle is not based on the signal measurement. Instead, it based on the movement of the target. There must a start point of the system. When the target have movement action, the distance and direction information can be added to the start-point to form the trajectory, and thus the position of the target can be known. This is especially useful for vehicles wheelchair or trolley localization. When it comes to walking people, there is an approach called pedestrian dead reckoning(PDR) which is one of the hot topic in indoor localization.

3.4 different positioning Schemes

3.4.1 schemes based on special infrastructures

In the beginning of the work, while mobile telephones were not so powerful as today, people are focused on approach which required special infrastructures. For example, infrared (IR) was used by Active Badge[47] to perform localization. Ultrasound devices was deployed by solutions such Cricket [48] and Active Bats to localize in the indoor environment and mobile devices. Recently, RFID became a hot topic and attracted many researchers. Solutions such as LANDMARC[49] and so on are very attractive. However, firstly, these solutions require these special devices make an extra burden for targets. In real environment, it is easy to forget these devices at home or in the car or on the desk. Or in some occasions, target refuse to carry them. So they may not assure a real-time reliability. Secondly, these systems require significant fund and effort which may hinder the development of themselves.

3.4.2 signal map or fingerprinting

The basic idea of fingerprinting is from scene analysis principle. It works in two phases: an offline training phase and an online localization phase[39]. During the training phase, signal strength or other distinctive features are measured at known locations, and these measured locations and features are stored as a database in a server. This database refers to fingerprinting map. During the online localization phase, when the target reaches a specific position and the feature of this position will be measured by devices and sent to server to check if there is a match or close feature can be found. If there is a such match, the position is decided[38].

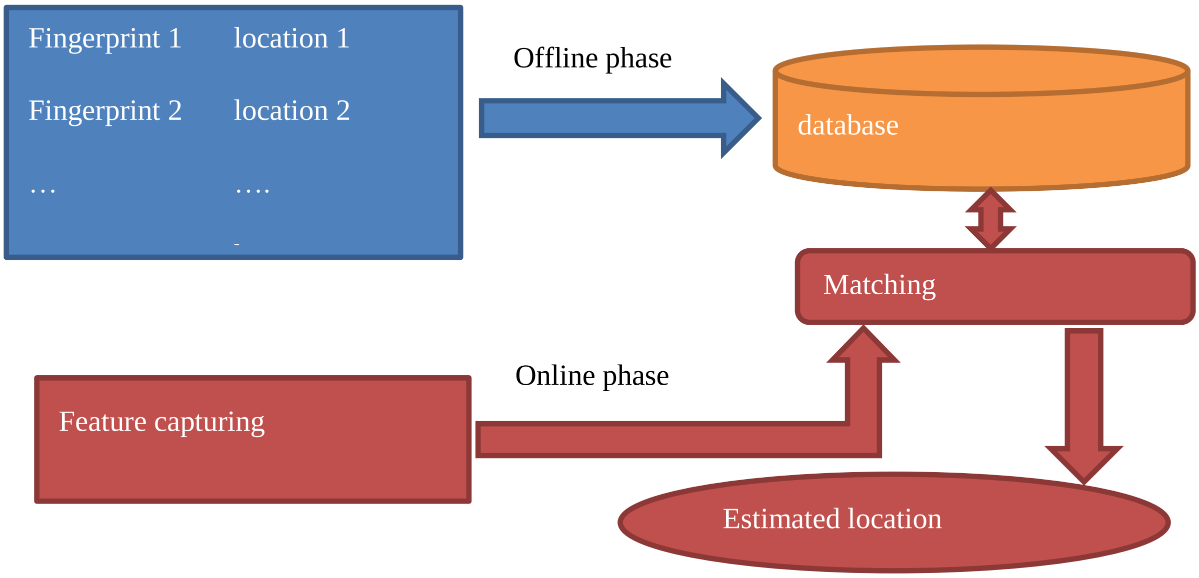

Figure 9 – fingerprinting procedures

There are mainly four kinds of fingerprinting approaches to create a signal map. First one is the traditional way which only rely on measurement to build the radio map. The typical case was RADAR[50] . Second one improves the traditional one by adding the parametric pathloss regression method. Third one applies non-parameter Gaussian Process(GP) regression to help creating the radio map[39]. In resent research, the fourth one is called SLAM (simultaneous localization and mapping) are proposed and attracted a lot of researchers[40][51] [52]. Among these signal map building approaches, the GP method is the most robust one[39].

There are few ways to decide the location of target, the most popular one is to compare the real-time captured feature with the data in the database by k-nearest neighbor (k-NN) algorithm[7][53]. Other approaches to match based on the way how the signal map was built are introduced in [39] and [40].

One fact that most researchers haven't paid attention is the time window of fingerprinting. That is how often to scan the signals. Due to the fact that different RF signals work in a different frequency, they may have different properties. And if the target is moving, the movement rate and distance have to be taken into consideration and the signal. Work which is done by Ramsey Faragher and Robert Harle [54] showed that Bluetooth fingerprinting has higher requirement on time window while it need less scan period.

3.4.3 Model-Based Techniques

Model-Based approaches are used for many kinds of dynamic systems for prediction, controlling or calculating. Model can be divided into three categories: white-box models, black-box models and grey-box models[55]. White-box models are those models we theoretical know the relationship between the know and unknow parameters, for example the RSS free space loss model. The black-box models are those kinds model we obtained from experiment, however there is no mathematical expression, for example the fingerprinting approaches is black-box modeling. The grey-box models those we partly know the model, it's a situation between white-box and black-box.

Model-based approaches is that the system tries to localize the target by the RSS value measured in real-time. It has a significant value because it can work without access to other sensors and it does not require so much labor work like fingerprinting approach does. These benefits attracted a lot of researchers' effort. Research from [8] showed it can offer a result similar to existing other methods. Researches from [56] showed that by model-based localization method can be built even without the cooperate of the access points[8].

In the previous sections, the model to calculate RSS value from specific distance was introduced. According to the trilateration principle, a location can be decided if there are three known distances. So there are many researchers try to use this model to predict or calculate the RSS value on different points, and use this to build the map or determine the location of target in real-time. It can significantly reduce the measurement from fingerprinting approach. Since RF propagation characteristics vary widely, the model parameters would have to be estimated for each indoor space in question.

There are mainly two well-known propagation models: free space path loss and ITU(international telecommunication union) models[57]. All model-based approaches have to solve two problems. How to decide the parameters and how to deal with the interferences from other objects. Simon Yiu and his colleagues [39] used a fusion method combined pass loss model with fingerprinting. Other researchers try to give model-based approaches self-adaptive capabilities[9][8].

3.4.4 Device free indoor localization system

In the previous discussed schemes, they have a same character that we all assume the target is carrying the mobile device. By locating the mobile device, we can locate the target person. Is that possible to achieve the goal when the person is not carrying the device? The answer is positive. There are researchers dedicated on those kinds of system called device-free techniques. It is called device-free[58] is because it does not require the target person to carry any device. However, the indoor environment still need APs (Access points) or Bluetooth signal transmitters to cover the area with RF signals and signal receivers to measure the changes of the RF. However, there is a lot of mathematical challenges.

Device free indoor localization was introduced in [59][58]. Device-free localization sometimes can be regarded as a subset of model-based approach and also can be called as ray-tracing. The basic of this idea is that our human body has specific influence on RF signals. Work in [60] showed that the human body can be modeled as metallic circular cylinder when consider its influence on RF signals. Before this system can work, fixed APs and measurement points should be set, then the RSSI values in the field should be measured or calculated by the model-based approaches. When the human enters the environment of interest, the influence can be modeled with Geometric Optics augmented with the Uniform Theory of Diffraction (UTD)[59][60].

Due to the principle that this approach depends on the human influence on the RF signals, the human body should be put between APs and measurement points. Research showed that in this kind of case, wall mounted APs is a better solution than roof mounted. Roof mounted design has a better opportunity to have LOS conditions. And due to the fact that the higher the radio frequency is, the better it goes through the objects, that leads to a less significant change in the signal. Device-free approach works better for those low frequency signals[29].

3.5 Topologies and ED positions

3.5.1 Tracking or positioning

A localization system can be divided into tracking and positioning system depend on who is the initiator.

When the initiator is an external party, the system is a tracking system or passive system. The passive system is that the user does not intended to be localized or they are intended to be localized but don’t give effort to help this work. For example, emergency rescue, iBeacon advertisement or customer behavior analysis systems. In this kind of system, the designer can’t expect the user to hold the device on hand and open specific app or even signals. For example, a lot of people may turn off Bluetooth function to save smartphone battery life. And due to that the ios system has a strict control of the Wi-Fi system, a lot of system which depend on monitoring the Wi-Fi signals may not work. This system may have issue with human privacy, therefor there is lots of challenges.

When the initiator is the user, this system is called positioning system or active system. The active system, on the other hand, is that the users themselves want to be localized. The best example is navigation system. They need to hold the device and run specific app in order to get the service. The customer can be asked to open some settings in the device to help improve the performance and accuracy. Because there is a app work in the localization system on the device, it offers huge amount of possibilities. However, power consumption may be a drawback and the system designer need to carefully consider about it.

3.5.2 Three topologies

There are three different system topologies for positioning systems[33].

(1) Remote positioning: In this system, the fixed devices or infrastructures measure the signals (AOA, TOA, TDOA or RSSI) and report to a center server. The signal available is limited by the measurement devices. Powerful and expensive devices is possible to be used. In the server,

a special program handles the data and give the location based on the required principles and different approaches. Passive localization is remote positioning.

(2) Self-positioning: In this system, the signals or other information for deciding the location are measured by the user's device. And the device computes the location based on different principles and approaches. The signals available is limited by the device, and the device may have a limit computation capability. But it is possible to use other approach such as magnetic sensor, motion sensor even microphone in the device.

(3) Indirect-positioning: this is a combination of the previous two topologies in order to overcome the limit of mobile devices. In this system, the mobile device can measure all the localization related information, and send them to a server. And at the same time, if it is possible, the signals from the mobile devices can also be measured by other devices. The server is in charge of computing the location and send the location to back to the mobile devices. An indirect-positioning system is a system which the mobile device measures the information but doesn't computer the position. But the mobile device gets the location from a server.

3.5.3 layout of external devices

Here the external device (ED) is used instead of access point, because in different approaches, the external device may refer to different things. In visual light communication based approach it refers to lights, in acoustic sound based approach it may mean sound resources, in Bluetooth based approach it may be iBeacon device or other Bluetooth devices. In a special cased called crowd sourcing, the ED is other mobile devices. Some of the mentioned ED is not controllable, for example, sound resource and other mobile devices. In those EDs that we can control, different design may lead to different performance.

ED plays a very important role in indoor localization system because it is the biggest hardware system in indoor localization. And this is also one of the limits of indoor localization. For example, ArrayTrack[61] has already achieved a 0.1 meter accuracy, but the multi-antenna router it used is expensive and not popular, so it can hardly be accepted. Visual communication system need to adjust the whole light system of the architecture, this also has a high cost. This is the reason why the Wi-Fi and LBE are the most popular approach. The Wi-Fi can deploy the current exist APs everywhere, which almost doesn't add any further cost. IBeacon devices is relatively cheap[45], but is still not be widely used yet.

In the topic about model-based localization and device-free indoor localization, we talked about the model of signal free space loss[57] and human-scattering effects[60]. This is what is happening all the time between EDs and mobile devices. In a device-free system, as it was said, LOS is the worst situation. So it is best to put the signal emitter and receiver in positions where human can mostly be between them. That's why wall mounting is the best solution. We may think it is better to use roof-mounted structure in mobile device-based approach and deploy as dense as possible. However, researches give a different result.

Work done in [62] showed that the accuracy can be increased by adding the amount of APs in the beginning, however, due to the increasing channel interference, the improvement will stop when it reaches a specific number. And this work also suggested to use orthogonal channel allocation, by this way, the accuracy can improve 10% and can reach the best accuracy with 15 % less APs than using adhoc and ascending channel allocation.

When consider about how to mount APs, work done in [29] showed a surprising result: roof-mounted APs design is not better than wall-mounted design. Although wall-mounted design may have a low possibility of LOS and higher chance to reduce the RSS due to attenuation, while roof-mounted design has a higher chance to meet LOS condition, their experiment showed that line of sight is not the most important factor in RF signal measurement.

3.6 Filters and algorithm

The challenges of indoor localization are the complicated indoor layout and moving objects such as human, this makes line of sight almost impossible between sensors and targets all the time. The RF signals can get through between targets and sensors despite the LOS challenge. However, it has a phenomenon called multipath propagation. That is the receiver will not get only one or two signals from the sender at once. The signal spreading on all the directions and reflected by objects and then some of the reflected signals go to the receiver with the main one if it is not blocked. And the signal is travelling in environment with human amount of noise.

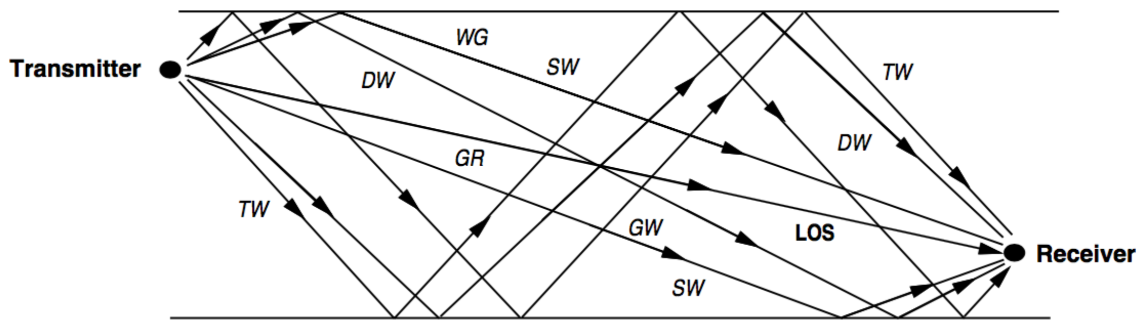

Figure 10 - Ten-Ray Model [63]

This forces an unfortunate trade off that most existing RF-based indoor localizations make: either model this hard-to-predict pattern of multipath fading, or leverage expensive hardware that can sample the wireless signal at a very high rate. Most of the researchers choose the former one. That's why they used very complicated model-based, fingerprinting with huge effort work, approximate to get a not precise result. Dealing with this challenge is not only the work for those work on indoor localization, also the work for signal processors and mathematics.

In this section, some mathematical approaches and how they are used to improve the performance will be introduced. Details about the mathematical knowledge will not be described, but articles about them will be recommended.

3.6.1 Gaussian Process Regression(GPR)

Gaussian process regression is a popular way to estimate or predict the unknow variables. One of the most famous and well accepted research to use Gaussian Process (GP) to estimate location was done by Brian Ferris[64]. His research showed that GP can offering continuous locations estimation in a wide range with an ability to correct uncertainty handlings.

In Ferris' later woke in [40], he proposed a Gaussian Process latent variable model to solve the Wi-Fi SLAM problem, although his result didn't show a good accurate, but comparing to other SLAM or fingerprinting approaches, his approach was extremely effective. And this can be a good implement for other work to improve the performance.

3.6.2 Kalman Filter and extended Kalman filter

Details and principles of Kalman filter can be read from [65], it will not be repeated here. The function of Kaman filter is to eliminate the noise caused by measurement and process, and use an estimator to estimate the state value of linear systems. But there is precondition, which is the average of noise should be zero.

When it comes to nonlinear system, an extended Kalman filter can be used. Sometimes, the application is not only to measure, but also to predict, then there came a modified version called Kalman smoother.

It can be shown that the Kalman filter minimizes the variance of the estimation error. A complementary Kalman filter is an easy way to integrate several sensors measurements in a Kalman filter because the internal structure of the filter is not changed[66].

3.6.3 Particle Filter

Kalman Filter works great in linear system. When it comes to non-linear system a lot of upgraded version are proposed such as extended Kalman Filter (EKF) [67], unscented Kalman filter (UKF) [68], Gaussian sum Kalman Filter (GS-KF) [69] and so on. But their performance in non-linear system is still not satisfying[70].

The particle filter (PF) is a classical object tracking algorithm for non-linear and non-Gaussian systems, which is an approximation of the optimal sequential Bayesian estimation via Monte Carlo simulations[71]. It works better than Kalman Filter in some aspect when the problem is non-linear. Or sometimes, the Kalman Filter can be used to measure the linear aspect of the problem and PF can be used to estimate the whole system[72]. More details about PF can be read from [70][73][71], it is not repeated here.

4 Smartphone based indoor localization

As we have discussed about device-free technique, special infrastructure based schemes. I believe the practical approach is to use device-based technique with our smart mobile telephones. There are mainly two RF signals which can be used for indoor localization. They are Bluetooth and Wi-Fi signal. A part of researchers is dedicated in one of these two platforms and they give their arguments. One part of researcher thinks it is better to combine them to achieve a better result. However, I don`t think we should limit ourselves since there are other information available on the smartphones. For example, the iPhone 7 is equipped with three-axis gyro sensor, accelerometer, proximity sensor, ambient light sensor, barometer. As the competition goes between smart telephone companies. These sensors will be equipped by all the smart phones and there can be more sensors.

In this part I would like to introduce pioneer work on indoor locations based on these sensors. Different from other surveys, instead of pointing out their problems, I would like to find out their positive sides for future choose when we need to design an indoor localization system.

Smartphone based indoor localization can be divided into two applications: tracking and navigation. Tracking is passive which means telephones are stored in the pockets or bags while navigation is active when telephones are hold on users' hand with app display on and special app is running.

It is possible to employ all the possible sensors when in a navigation application where the users are willing to assist the system to get a better accuracy. The system can ask the user to turn on Bluetooth, give access to the camera or microphone and so on. However, in tracking application it is possible that the Bluetooth is turn off, camera can't work for indoor localization when it stays inside the pocket or bag.

Although the process ability and cache of modern smart phone are improved at a quite surprising speed, some of them can almost beat normal laptops, they are limited by the battery capacity. Therefor, power consumption has to be taken into consideration when design a smart phone based indoor localization system. Sampling frequency, computation has to be reduced while chasing the best performance.

There are mainly three smart phone systems. They are ios, android and windows phone. The ios system is quite closed and completely controlled by apple. As a side effect of that, some approach may not work on this platform, for example, Wi-Fi fingerprinting.

4.1 Camera and visible light-based approaches

As a human, our first experience of localization is to use our eyes. Using camera is a good imitation. Since this chapter is talking about using sensors on the smartphone, the approaches which uses camera on the wall will not be talked her. The system her is to use the camera or light sensor on telephone to locate itself. It is a positioning system. The main idea in the back of this approach is a technology called visible light communication(VLC) [32].

In [74], author introduced a smart LEDs based localization system by using the visible light from light systems called Epsilon, which an available in almost all the indoor environment. It uses the trilateration principle which means at least three anchors are needed in order to achieve position determining. The distances between the target and anchors are calculated by RSS-based technique which based on the RSSs from the light which was sensed on the smart telephone. Different anchors are identified with different emitting frequencies which have to be over 200 HZ in order to avoid flicker to human eyes and stay away from sound frequency (50/60). But the sampling frequency of sensors on the smart phones are not so high, several hundred HZ. So the available designed frequency is limited in this range. This system makes use of the light infrastructure of buildings or other indoor space, reduces the requirement of radio frequency devices and signal interference, achieved a sub-meter accuracy. This system requires devices in a light of sight (LOS) scenario and have at least three LOS LED anchors. Furthermore, for those situations such as telephones in the pocket or blocked by bodies or other objects, it can hardly work.

In [75], the author offered an improved visual localization system with image processing technology. It deploys the camera on the smart telephone and the around infrastructure: LEDs. The basic approach is to take pictures with several led anchors and the target inside. The anchors are configured into different frequencies. So that the system can know where the anchors are and by using image processing technology, distances between the object and anchors are got. So can the system know the exact position of target. With an enough number of anchors in the picture, Luxapose is able to achieve a 10-cm accuracy indoor positioning. What is more from this system is that, the system can figure out the orientation information which not available in lots of solutions. By comparing the coordinate axis in the image with the ground truth, Luxapose is able to determine the mobile's orientation to an accuracy of 3◦. A similar system developed by Philips was deployed at Carrefour[76].

Due to the limit of LOS and benefit of accuracy, it is great for those applications which users would like to take it outside pocket such as indoor navigation, traveler guiding and so on.

In [32], plenty of VLC based positioning systems are introduced. And a lot of them provide much better accuracy then other approaches. However, Luxapose is based on windows phone system. Android and apple IOS does not give the API to get access to full camera control. Their visual light approaches are based on a special device photodiode (PD) which is not integrated inside smart telephones yet. So as shown in the illustrating video of Philips VLC based indoor localization system, camera-based approaches are more practical.

4.2 Bluetooth low energy (BLE) for indoor localization

4.2.1 BLE

In recent years, low energy wireless communication technologies are one of the hot topics due to the coming internet of thing (IoT). ZigBee was regarded as the best option of future industrial wireless communication standard. However, it shows that it has its own problems. At the same time, there came a new standard of Bluetooth, which named as Bluetooth low energy (BLE) aiming to replace the main role in IOT communication. The low energy version of the Bluetooth that is specified in version 4 is known as Bluetooth Low Energy [8]. The core of the improvement of Bluetooth 4.0 standard is "low power", "long distance" and "high speed start". Indoor positioning based on Bluetooth 4.0 only need 3 ms connecting time and it can cover 100-m area.

Nokia is one of the representatives of the BLE technology, who once launched the HAIP (High Accuracy Indoor Positioning) indoor precise positioning solutions based on Bluetooth triangulation technology in 2012. HAIP achieves 0.5m to 1m location accuracy. However, due to the low popularity of the Bluetooth base station and high indoor precise positioning costs, the solution has not been practically adopted.

BLE system can detect and detected, so it can be used as both tracing and positioning. However, not all people like to turn on Bluetooth based on the concern of power consuming. That makes it sometime not work for tracing applications. In positioning system, users can be asked to turn on Bluetooth for the localization app.

4.2.2 iBeacon

In 2013, Apple introduced their term called iBeacon which based on the technology Bluetooth low energy beacon. iBeacon devices emit beacon signals that can be picked up by a BLE-enabled device within a close range. Apps can be built to cause events to be triggered within an instant of a device coming within the detectable range of the beacon.

Moreover, the device is able to calculate how near or far away it is from the beacon, meaning that different events can be triggered depending on whether a device is within, say, 5, 25 or 100 meters of a BLE beacon. A device can identify numerous beacons simultaneously and, by calculating its relative distance from each of the beacons, the device can gain an element of location awareness.

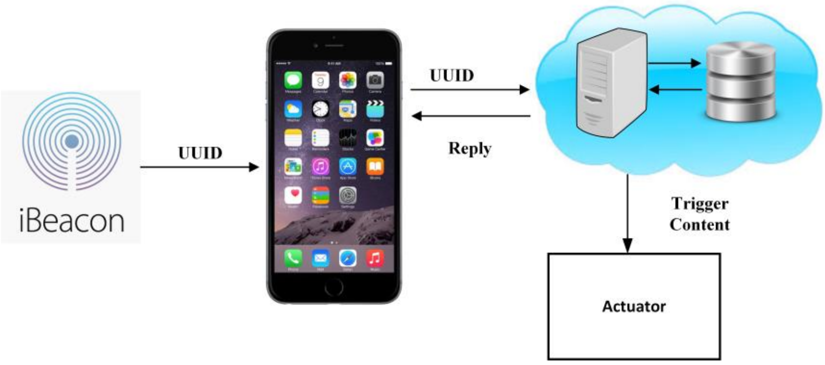

Figure 11- structure of iBeacon system[77]

User can build a base signal station and holds the IOS or Android device to enter the area, where they will get information from the base station.

4.2.3 Improve iBeacon based indoor localization

According to the diagram offered by apple, iBeacon just offers four proximity states: immediate, near, far, Unknow. This is far less than enough to localize target in real-life situation.

Proximity State	Description
Immediate	This represents a high level of confidence that the device is physically very close to the beacon. Very likely being held directly up to the beacon.
Near	With a clear line of sight from the device to the beacon, this would indicate a proximity of approximately 1-3 meters. As described in the section on accuracy, if there are obstructions between the device and the beacon which cause attenuation of the signal, this Near state may not be reported even though the device is in this range.
Far	This state indicates that a beacon device can be detected but the confidence in the accuracy is too low to determine either Near or Immediate. An important consideration is that the Far state does not necessarily imply "not physically near" the beacon. When Far is indicated, rely on the accuracy property to determine the potential proximity to the beacon.
Unknown	The proximity of the beacon cannot be determined. This may indicate that ranging has just begun, or that there are insufficient measurements to determine the state.

Figure 12 - proximity states of iBeacon[78]

Therefor a lot researches are done to improve the performance.

Faheem [10] applied Server-Side Running Average (SRA) and Server-Side Kalman Filter (SKF) on iBeacon based indoor localization system. Improved the proximity detection accuracy of iBeacon by 29% and 32% respectively.

Quanyu Wang[72] used cascaded Kalman Filter-Particle Filter (KFPF) algorithm for indoor localization. The Kalman Filter (KF) reduced the RSSI fluctuation and then the filtered RSSI values was input into a Particle Filter (PF) to improve the accuracy of indoor localization. They achieved a 1.03-meters average 2D localization error and a 1.33-meters average 3D localization error in a replicated real-world scenario.

4.2.4 other BLE based indoor localization

Since iBeacon is a packed technology and the performance is not so satisfying, there can be more possibilities to focus on BLE based indoor localization.

When Bluetooth is on visible state, BLE advertisements are broadcast on three 2 MHz advertising channels in quick succession. These channels are nominally labelled 37, 38, and 39 and are widely spaced at 2402 MHz, 2426 MHz and 2480 MHz, respectively[54].

This gives the possibility to use Trilateration, Triangulation and scene analysis (proximity principle is used on iBeacon) principles to decide the location.

In [79], the author installed Bluetooth scanners inside a shopping mall to track human trace inside in order to analyze human behavior. His approach based on approximate principle. Log of detection of devices are saved insider the scanners. And the path can then be reconstructed by combining the logs of all scanners, where the location of each scanner is added as the location of the device.

Ramsey Faragher and Robert Harle [54] used fingerprinting approach achieved a 2.6 m error 95% for a density of 1 beacon per 30 m^2. Their research made an excellent example of BLE fingerprinting by taking into consideration of time window, movement speed, fast fading and so on.

Jun-Wei Qiu [9] proposed a self-adaptive approach to decide the parameters of signal propagation model. He built a dynamic model based indoor localization system. His experiment showed that this can improve the ranging error in a relationship with the distance of the extra sensors and number of regression samples. By utilizing the adaptive ranging with device-specific parameters has an improvement of approximately 19.99% in accuracy

4.3 WIFI based indoor localization

Wi-Fi router and access points (APs) are almost everywhere nowadays. The high percentage of coverage in architectures makes it one of the best candidates for indoor localization. Wi-Fi based indoor localization system can be used anywhere there exists Wi-Fi infrastructures. Due to the fact Wi-Fi give mobile device a non-cost high speed online experience, the most mobile device user would like to keep Wi-Fi function on and connect to any available APs, this makes it possible to design both tacking and positioning system.

In January 4, 2016, Wi-Fi Alliance announced a new low power Wi-Fi standard called Wi-Fi HaLow [80]. The new standard extended Wi-Fi into 900 MHz band which will be considerably with lower speed but longer range. These new features give Wi-Fi a potential to offer better indoor localization system by lowering the power consumption, increasing the user acceptance, improving the object penetrate ability and reducing the AP number and cost while keeping the same coverage inside the architecture.

In order to use Wi-Fi based indoor localization, RSSI or AOA/TOA may need be measured. In Wi-Fi standards, there are no definition of how RSSI should be achieved. Different hardware supplier may use different ways and there can be different results when measure a same position under same situation with different hardware. It is important to be aware of this when design the system. Another obvious factor to effect RSSI measurement is the material of smartphone, metal case and plastic case may have different effect. When design a positioning system, being aware of the brand and model of the telephone can give a better judgement of the case material.

There are currently two open source tools to customize router or Wi-Fi APs, they are OpenWRT[81] and DD-WRT[82], they can help engineers to customize current available devices to reach the goal.

4.3.1 model based indoor localization

As it was discussed in part 3, model-based approaches are popular due to it does not need hard work to analyze the scene and huge amount of labor to collect the field information. Work done by Jure[8] gives the newest research based on model-based Wi-Fi indoor localization and there are a lot of introduction of related work, detailly discussed the advantages and disadvantages. He utilized free space path loss and ITU models and gave an improvement by adding two additional parameters. At the same time, in order to have a better dynamic self-adaptive model, RSSI signal from other APs are analyzed to infer the parameters of the space in the path loss. A third-party router firmware called OpenWRT [81] was used to modify their APs so that they can turn these Aps into monitor model and manually decided the channels for the system. In the end, they got a mean error of 2-3 and 3-4 m respectively.

4.3.2 AOA and TDOA based estimation

The smartphones are not equipped with enough good and amount of antennas to measure AOA and the software system can't assure a fast enough respond to achieve TOA or TDOA approach. The only solution is to leverage external devices and this is expensive.

Arrat Track and ToneTrack maybe are the best examples of AOA and TOA based smartphone indoor localization system currently. The author used multi-antennas routers, which are built on top of WARP software-defined radio platform developed by Mango [85], to measure input signal RSSIs. In the ToneTrack system, the principle of how to measure AOA through a multi-antenna device and the algorithm was detailly described. With his approach, this system achieved 38 cm accuracy with 6 APs in the end.

In ToneTrack, multiple signal classification (MUSIC) and matrix-pencil are applied and improved for this project to reduce the channel-scanning time, which is one of the limit of Wi-Fi based indoor localization approaches. In his field test, the system was able to achieve 0.9-meter median accuracy in a typical office environment with strong multipaths.

4.3.3 WIFI signal fingerprinting approach for indoor localization

RADAR[50] from Microsoft Research is one of the first deterministic Wi-Fi fingerprinting based approaches in indoor localization history[58]. After RADAR, huge amount of work are done in order to improve the accuracy or reduce the training work. Horus[83] used a location-clustering technique to reduce the labor work and computation while increase the accuracy. Crowdsourcing which was proposed by [84] tries to utilize users' mobile devices to collect fingerprinting and upload to a server where a database and radio map can be built. It is proved that this approach can significantly reduce the labor that is required to build fingerprinting map[85]. More work about crowdsourcing can be read from [86][87][88][89][90].

In [91] the user was dedicated to improve Wi-Fi signal fingerprinting performance by an invariant RSS statistics method. His proposed was tested by an android smartphone (A Samsung Galaxy S4 smartphone with Android version 4.4.2) and achieved 90% success rate at 3.7-meter resolution.

However, not all mobile platforms allow access to the Wi-Fi scan data. Apple's iOS, for example, allows only RSS readings from the connected access point, which prevents third-party Wi-Fi fingerprinting[54]. Therefor smartphone based WIFI fingerprinting is only suitable for android, windows phone or Linux system devices.

4.4 motion sensor based indoor localization

Nowadays, the most smart-telephones are equipped with multiple motion sensors such as three-axis gyro sensor, accelerometer. By analyzing the information from these sensors, carrier's motion dynamic information(MDI)[13] can be access, therefor we can infer the real-time position of the target by combining the MDI and building map information (BMI)[28]. For example, a man went into the door and step inside 3 meters. It is not hard to put him on the specific spot on the map of the building.

In this example. We need three information: the start position (reference point), the direction of target's motion, the speed of the target or the distance the target has gone.

4.4.1Reference points

There must be at least one reference points that the system can detect when the target is on these spots. This point or spot is the start position the system uses to "calculate" the further real-time position. In the purely motion sensors based indoor localization system. The estimate error accumulates and this has no way to fix it. There must be a few reference points as check point for the system to reset the current position of the target. The more reference points available in the building, the higher accuracy can be reached, while the higher cost will be for the system.

The reference points can be designed to be automatic done by using Wi-Fi[92], Bluetooth[93], audio or other indoor localization method. Losing signal of GPS can set as a start point of indoor localization. But these approaches are inaccurate, therefor the error will accumulate as the system works. In [86] author suggested a landmark detection approach by crowd sensing and defining identifiable signature of special location such as stairs, doors, elevators and corners. His approach reached a meter level accuracy. VLC approach may offer cm level accuracy, it can be used if possible.

Manually calibrating methods can give a better accuracy, while reduces the user experience. This can be done by user scanning the QC code, or "putting" himself/herself on a specific landmark[15].

4.4.2 Heading (Direction)

After the system has detected the target on the reference point, the direction of the future motion is import because it decides where the distances should be added on. And when the target is turning, the system has to acquire this action.

An absolute direction can be directly measured or estimated by a digital compass, while a relative change in heading can be measured by gyroscope sensors. However, Due to the interference of external magnetic, large-scale iron, steel equipment and so on, the magnetometer output is not stable under indoor circumstance and there exists large deviation, which will directly affect the position estimation accuracy.

A gyroscope can be used to measure a relative direction change with no impacts from the environment but the drift error will grow with time. In [94], the authors introduced a fusion algorithm by taking both magnetometer and gyroscope sensors into consideration. It is

$$h_k^D = w_0 h_{k-1}^D + w_1 h_k^g + w_2 h_k^m \tag{8}$$

Where w_i, i=0,1, 2 are weighted factors and $w_0 + w_1 + w_2 = 1$. h_k^D represent the current direction, h_k^g is the direction change measured from gyroscope and h_k^m is the direction change measured form magnetometer.

According to his experiment, this algorithm gives a better result than use just gyroscope or magnetometer[94].

4.4.3 steps measurement

In order to detect the steps, it is good to observe how people walk first. There are two phases:(1) One of the feet raises while the other one stays on the ground;(2) The body lean it towards the front and the foot hits the ground[13]. When the foot hits the ground, vertical acceleration signals with periodic patterns will be detected by the three-axis accelerometer in a smartphone coordinate system(SCS). This SCS can be transformed into earth coordinate system by applying a rotation matrix[93], and it will be look like shown in Figure 13 .

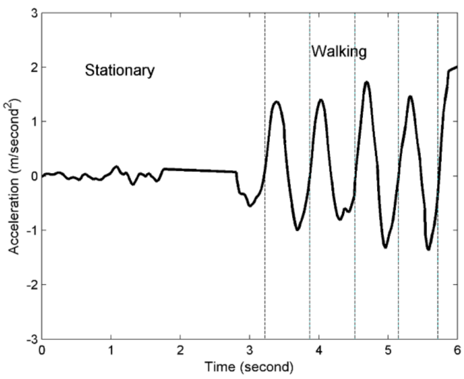

Figure 13 - The acceleration patterns of a pedestrian in stationary and walking states[13]

Another problem of step detecting is that this result contains earth gravity. It is difficult to separate pedestrian acceleration from that of gravity because the sensor attitude is unknown[13]. But the gravity in one area is relatively stable, this makes it possible to eliminate it. Chen[93] applied low-pass filter to remove the gravity and Liu [13] used average of acceleration norm to estimate the magnitude of gravity.

4.4.4 Step Length Calculation

There are plenty of ways to determine the step length, one of the most used one is

$$L = \delta * \sqrt[4]{Acc_{\max} - Acc_{\min}} \tag{9}$$

where $\delta = \frac{d_{real}}{d_{estimated}}$ and should be computed in advance for different users; d_{real} and $d_{estimated}$ are real walking distance and estimated walking distance, respectively. $Acc_{\max}$ is the peak value of acceleration and $Acc_{\min}$ is the bottom value.[95][96][97][98].

Some improved methods are introduced in [99], for example Kim's algorithm[100] and Tian's algorithm[101]. Work done by Ho[99] gave us a way to detect step length in a more adaptive and accurate way. However, utilization of fast Fourier transform(FFT) makes it power consuming. The future system can use an indirect-positioning topology to work.

4.4.5 position determining

After knowing the start point, heading direction, step length and steps, it is not hard to decide the current position of the target. However, this approach is an open-loop system which means there is no way to compare the calculated trajectory with the real trace except when target reach the reference points. The accuracy depends on the calibration design.

Mostly, motion based indoor localization works with other sensors such as Wi-Fi and Bluetooth. Researches show that a fusion system of motion sensor and Wi-Fi can approach a better performance[92][13][102].

4.5 Audio (microphone sensor) based indoor localization

Comparing with camera or light-based approach, audio approach is more stable to the change of context, as shown in Figure 14. This gives us more confidence to develop audio (microphone) based indoor localization system.

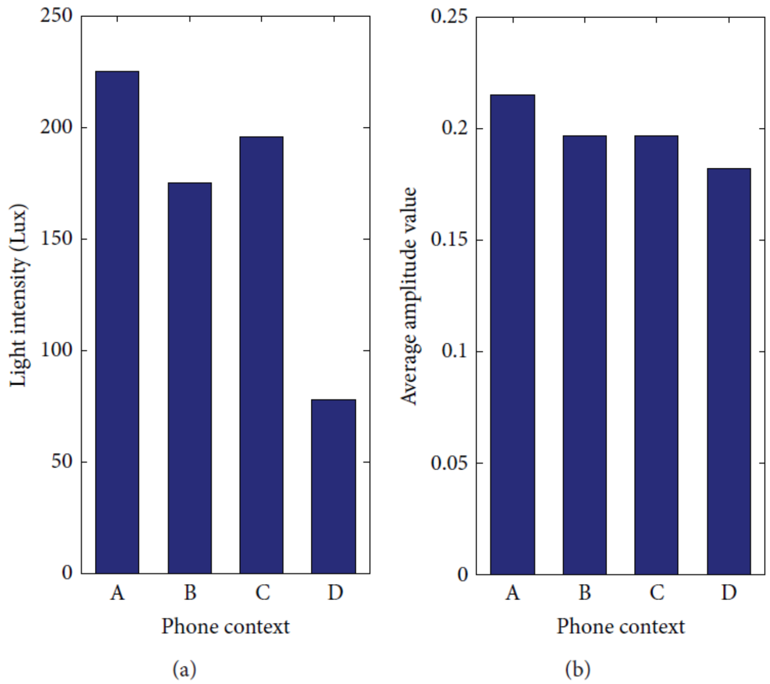

Figure 14 -The influence caused by changing contexts of mobile phone[103].

The context represented above is:

(A) in the hand of the user facing the source

(B) in the pocket of the user facing the source

(C) in the hand of the user facing away from the source

(D) in the pocket of the user facing away from the source

The first acoustic-based localization system was introduced in [104], they place microphones at key locations and users snap their fingers to give the system audio information, and then the position was detected.

The microphones on modern smart phone, for example iPhone 6s, is able to sample at 44.1 kHz[105]. According to the Nyquist-Shannon sampling theorem [38], the microphone is able to capture information under 22 kHz, and, as a result, it can capture and recognize not only human speech, but also high frequency sound like music and machine. Therefor, current smart phone can play a good role in sound sampling and recognizing.

4.5.1 audio based TDOA approach

Although sound based signal forms a field like other RF signals, it has a special advantage of utilizing TOA or TDOA approaches. That is because it travels in a much slower speed than light. This significantly reduces the requirement of timer on mobile devices.

According to [106][107], they have successfully localized a group of mobile devices with only ambient sound and a Wi-Fi network. The method they used is called Ellipsoid, which is a TDOA-based method. By using at least four receivers with unknown positions, they successfully localized four apple laptops and four iPhones with a positioning accuracy of approximately 0.28 m.

The Apple products are equipped with High Precision Event Timer (HPET)[108], which makes high accuracy timer synchronization possible for TOA/TDOA approach. And iPhone have an good inbuilt audio pipeline and this makes it have very little input latencies. Work done in [107] were able to synchronize the devices within an accuracy of 0.1 ms through the Network Time Protocol (NTP). However, in Android system smartphones, this accuracy in time synchronization, even utilizing the NTP, is currently not possible, and the measurements are very noisy[109].

In [109], the authors developed their localization system in the native layers of Android using the Native Development Kit(NDK) in order to reduce the overhead latency of audio data collecting. In [110], the authors introduced a hybrid system called NEST which used image and audio approach on Android device. In the acoustics-based part, the devices are used as anchors at known locations to estimate the sound source location. The TDOA was estimated by identifying the peak location where the maximum of the cross-correlation between the two signals occurs. The recorded sound events and corresponding time stamps were processed on a common smartphone which acted as a master in the system and the Fast Fourier Transformation (FFT) filter was deployed to reduce the computation. Synchronization offset and start time error between devices are estimated and subtracted from time delay to calibrated TDOA for the positioning of the source. Their acoustics-based system achieved a ±15 cm in the x-direction and ±80 cm in the y-direction. The accuracy in the x-direction is better because the sensor array baseline is relatively short compared to its range to the source.

4.5.2 audio based fingerprinting approach

As it was said before, the audio information can be also regard as some kind of field, where there is field, there can be a field map of signals. However, different from other signals, sound information is complicated. Firstly, the sound signature of a place is almost unarrangeable. For example, some place such as home, museum or theater may be quiet most of the time, which means there can be totally no sound information to utilize. In the public place such as shopping mall and airport, there can be too much noise which is require heavy computation to process, which is challenge to smartphone due to is limited process ability and battery restrain. Special infrastructures which generate regular sound information can be annoying even health harness for human beings.

Secondly, privacy can be a problem since the sound may contains some sensitive private information, thus a sound based indoor localization system must solve this problem before it can be accepted by the users.

But there are still possibilities. A DECENT acoustic fingerprinting technique called Acoustic Background Spectrum(ABS) was introduced in [111]. It firstly calculated an acoustic spectrum and then filtered the transient sound so that it can be time-invariant.

In [103],the author tested the relationship between sample time and accuracy and power consuming. They found out that 15s can offer a good accuracy with a reasonable energy consumption. In order to achieve high accuracy, target's schedules were acquired and fingerprinting data were collected and stored in a backend server. The most computation work are done in the server instead of telephone so that it can offer a better computation capacity and low power consuming on the telephone part. The system approximates the place where the user is by detecting the specific background sound in the environment or analyzing the speakers' identity by the content of speech. The background noise was filtered by typical Voice Activity Detection(VAD).

In [46], author introduced sound sense which collects sound data by the microphone and uses time-domain and frequency-domain feature of the sound. Instead of getting an accuracy localization result, they used approximate principle to decide a room level result.

4.6 Magnetic field based approach

We are living under a nature magnetic field, which is also possible to be used for localization[112][113]. The magnetic field covers the whole earth, that offer it a chance to be used everywhere without any limit. Campus was invented by Chinese thousands year ago and they are offering navigation service in wild area. Not like wild area where there is no interference for magnetic-filed from metals and electric devices, indoor environment is complicated, there is no pattern for the field distribution in indoor scenario. However, this uniqueness gives the chance for fingerprinting approach to show its value. The more special the indoor magnetic-field-distribution is, the easier for fingerprinting approach to build a special database or field map and this map is tested to be stable by[112]. An indoor localization system based on RSS-Magnetic fingerprinting was introduced in [113].

Mostly, magnetic field approach does not work alone because it has a possibility to mismatch(target can be located in a wrong building[112]) . A lot fusion system can take magnetic field into account such as work done in [114],[115]. The more detail about fusion system will be discussed in next section.

4.7 Multi-approach indoor localization

In the previous sections, indoor localization based on every sensor in the smart phones are introduced. They all have their advantages and disadvantage. That is why there is still not a standard for all the applications. But how about we utilize not only one sensor for the localization work? Then it comes to a topic about multi sensor approach, which use a combination of more than one sensors as complement to each other to give a more robust and accurate result.

Actually, multiple sensors and signals of opportunity have been used for indoor positioning and navigation applications since long time ago and the researches on this topic has been taken for many years [116][114]. Examples of such sensors include accelerometers, gyroscopes, compasses, cameras, proximity sensors, and electromyography sensors as they were introduced in the previous parts. The studies presented in [117][118][119] show that positioning accuracy can be improved by the incorporation of current RSSI measurements in conjunction with knowledge of motion dynamics and historical measurements.

There are mostly three ways of utilizing multi-sensors:

(1) SLAM: As it was said that fingerprinting approach has a main disadvantage that it requires too much labor to build the signal map before it can be used. So one of the solutions is using other available sensors to localize itself before the signal map was built and in the meanwhile collecting the RSSI information and upload to the server where signal map is built. This is called Simultaneous Localization and Mapping (SLAM)[120].

(2) Fusion: All the sensor that can be used can make their contribution to the final result. That is to take all the localization information into account and evaluate the most likely position of the target. For example [13][113][92][94].
(3) Multi-availability: when one sensor doesn't work, then use another. For example, sometimes Bluetooth can't be used due to that the user turned it off, and Wi-Fi is available, then can use Wi-Fi as the main approach. Or there can be sometimes neither Wi-Fi and Bluetooth works, then utilizing other sensors become the only solution[121].

4.6.1 SLAM with multi-sensors

Fingerprinting can offer a relative accurate indoor localization result with low computation and high respond speed. However, the creating process of the signal map is time consuming and requires huge amount of labor work. The idea behand SLAM is to use other available resource to obtain the signal map. When it comes to smartphone perspective, the available sensors are mainly VLC based (4.1), motions sensors (4.4) and magnetometer.

Faragher[51] proposed a hybrid system which used a hip-mounted IMU to obtain the location of user while the user uses smartphone to measure the RSSI. He used a distributed particle filet to filter the drift error of IMU approach and suggest the user to revisit the locations to help the system to observe and correct the drifts.

Mirowski [15] built a system on Android phone which can gather fingerprinting of Wi-Fi RSS, Bluetooth RSS, 4G LTE RSRP and magnetic field magnitude by the information from IMU and pedestrian dead reckoning(PDR) approach. The user just need to keep the smartphone inside the pocket, while a lot of article require the user to hole it in hand in order to have a better accuracy. They used a modified Graph-SLAM[122][123] to synthesize the measurements from different sensors and infer the trajectory.

4.6.2 Fusion solutions

Scholars have noticed that magnetic matching (MM) results have small fluctuations[113], but it have a risk of mismatching due to low magnetic fingerprint dimension[112], in contrast, Wi-Fi results have a low mismatch rate but suffer from larger fluctuations [124] (The term "mismatch rate" means "the percentage of position results that have a position error of over 15 m")[114]. Therefore, there is a potential to use Wi-Fi for a rough positioning, and then use MM for a more precise localization. Article [114] proposed a fusion system which combined PDR,Wi-Fi fingerprinting and magnetic matching (MM) approaches to use off-the-shelf sensors in consumer portable devices and existing Wi-Fi infrastructures.

WAIPO[14] is an indoor localization system with the fusion of Wi-Fi and other in-built sensors such as camera, Bluetooth, accelerometer, magnetometer for surrounding sensing, which is easy for promotion and application [26]. The system utilized a User Location Preference (ULP) model with fingerprinting data from other sensors to gather users' location preference. When localization service is need, it estimates the location by sensing the co-occurrence and non-concurrence people around.

HIPE[13] is a hybrid approach fusing a smartphone's motion sensors with Wi-Fi fingerprints. The smartphone's motion sensors measure the user's motion dynamics information, such as step count (by an accelerometer) and heading direction (by a digital compass). To perform the fusion of motion information for position estimates, a hidden Markov model is used along with a grid-based filter algorithm and the Viterbi algorithm.

For the integration of different localization results, the literature [125] uses a Kalman filter to fuse the information from different sensors[66], while the research [15] utilizes a bundle adjustment approach to implement simultaneous localization and mapping.

5 Design of indoor localization

All the technologies are developed to solve some problems or make contribution to the world. This need to done not only by developing the science, but also by applying the knowledge in real environment. That why this article is always talking about those really realistic approaches by focusing on smart telephones.

In the previous parts this article has concluded the knowledge structure of indoor localization with citations. The aim of the previous part is to help the reader to have a comprehensive understanding of indoor localization in a wide range.

This part tries to use the above knowledge to solve real engineering problem, explain how to design a indoor localization system. In this section, some question about (1) the processing of designing the system; (2) approaches to improve the system (3) standard to evaluate the system will be answered.

An example of designing one indoor localization system in UiT Narvik campus will be introduced to illustrate stated principles and procedures.

5.1 the processing of designing the system

When it comes to the procedure of designing an indoor localization system, there can divided into the following 9 steps:

1) Need analyzing: In this part, the needs of the application should to be listed. Different applications may have different requirement on accuracy and approach availability. For example, teacher locating at school may require room level accuracy while customer shopping intention monitoring may require cm level. Audio based localization maybe an awful idea in museum but can be good a busy shopping mall to detect which shop a target is.
2) Field inspecting: this helps to find the resources available in the current system building. Wi-Fi APs, iBeacon devices light system, acoustic sound distributions can be listed as candidate resources.
3) System structure and topology decision: Firstly, it is a tracking system or positioning system need to be decided. Secondly, which topology should be used for this system. Thirdly, the designer can search for possibilities to improve the system by modify the layout of external devices.
4) Device/devices and sensors choosing: Sensor-availability is limited by the device. And mostly, practically, smartphone is the best choice. In some occasions like huge supermarket or airport, targets may use extra device like charts, additional sensors are possible. When the device is decided, the program platform is also decided (ios, Android or Windowsphone for mobile device system or windows and MacOs for laptop). Which sensor to choose sometime is depend on the infrastructure such as Wi-Fi and Bluetooth. And it is also limited by the topology of the system. In a tracking system, camera and IMU may not be available.
5) Principle decision: There are five principle options as introduced in 3.3. The designer decides the principle according to the need and sensors.

6) Schemes decision: Device free approaches is not considered in this paper. So there are only fingerprinting and model-based schemes. However, this step may be not needed if the system uses proximity or trajectory principle.
7) Basic technique achieving: There are five basic techniques for choice. But trajectory principle doesn't require this step.
8) System performance evaluation: After a system building process, the system should be tested in different situation and performance in accuracy, power consumption, users' experience should be evaluated. When the system works well in experiment environment, it should be tested under real target environment with normal condition (crowed people do whatever they are supposed to do under the system).
9) System improving: Redesign the system from step 4 or try to improve the system by a) utilizing a filter or better algorithm b) adding fusion solutions 3) improving the topology or external devices.

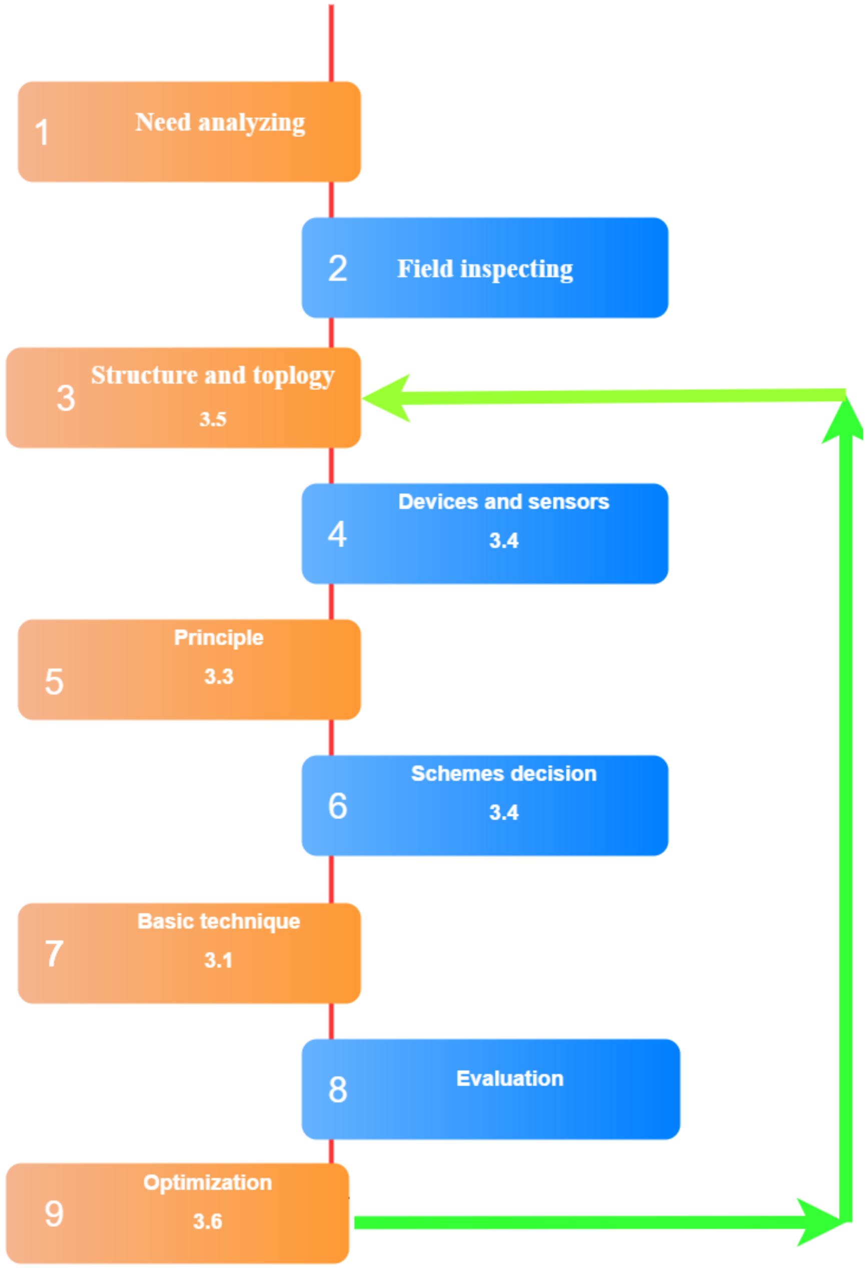

Figure 15 Design flow of indoor localization based on this paper

5.2 example of UiT Narvik campus

5.2.1Need analysis:

Application	Accuracy	Passive/Active
Students' attendance	Room level	Passive
Where to find teacher	Room level	Passive
Anti-cheating on exam	1 m^2	Passive
Emergency rescue	Room level	Passive
Guests/New student navigation	1 m on aisle, room level when in classroom.	Active

Table 1 – need analysis of UiT Narvik campus

5.2.2 source analysis

(1) Device: It is not realistic to ask students to carry special device. Everyone has at least one smart phone with them most of the time when they are at school. And these smart phones are connected to the school's WIFI APs. So smart telephone is the best choice in this case.

(2) Sensors:

a) WIFI: According to the current situation in the campus, there are plenty WIFI APs around to offer WIFI coverage every inside the campus.

b) Bluetooth: There is no Bluetooth device coverage. Need extra cost to implement Beacon devices inside campus.

c) VLC: Lights are available everywhere and all the time. Need extra expense to modify the light for VLC system and only possible to be used for navigation application.

d) Microphone: Environment sound signatures can hardly be defined, most of the classrooms have the same property and it can be quiet everywhere sometimes.

e) Motion sensor: Can be used for navigation application. It is not dependent on any special infrastructure. Reference point need to be implemented to offer a better accuracy. One of the reference solution is to use the front camera to detect room number and doorframes. Every time when camera detect a room number or doorframe, the system can calibrate target's position and direction.

(3) Schemes:

Model based: This can meet the most room level requirement except the anti-cheating and navigation applications. Positioning work can be done by server which accesses data from APs.

Fingerprinting: This is possible to get a higher accuracy, however, RSSI map changes between class time and break time and after all the classes are finished. This means it may need to create more than one map. This makes it too much labor requirement. Especially in country like Norway, human labor is too expensive.

AOA, TOA or TDOA: the current APs at school are not equipped with multi-antennas.

(4) System principle:

For room level need, proximate principle fits well. Navigation application, however, according to the analysis above, the best solution is to use “motion sensor + camera” to get high accurate result. So this is scene analysis. There is one need that we can hardly meet the requirement. That is the anti-cheating application which requires 1 meter accuracy. It may take huge expense to fulfill the task. Alternatively, we may divide the classroom into two parts, which is the front part where supervisors are and the back part where all the students are. Cheating detection can be defined as smartphone in the back part of the classroom during exam. This can help teachers to make sure no one carrying smartphones or other Internet-enabled devices before exam starts. So proximate principle applies.

5.2.3 system decision

According to the analysis above, it is not hard to draw the conclusion that this indoor localization system should use smart phone, WIFI-RSSI model, based system using approximate principle for passive applications. When navigation application is called, smart phone app use inbuilt motion sensor and camera to improve the positioning accuracy.

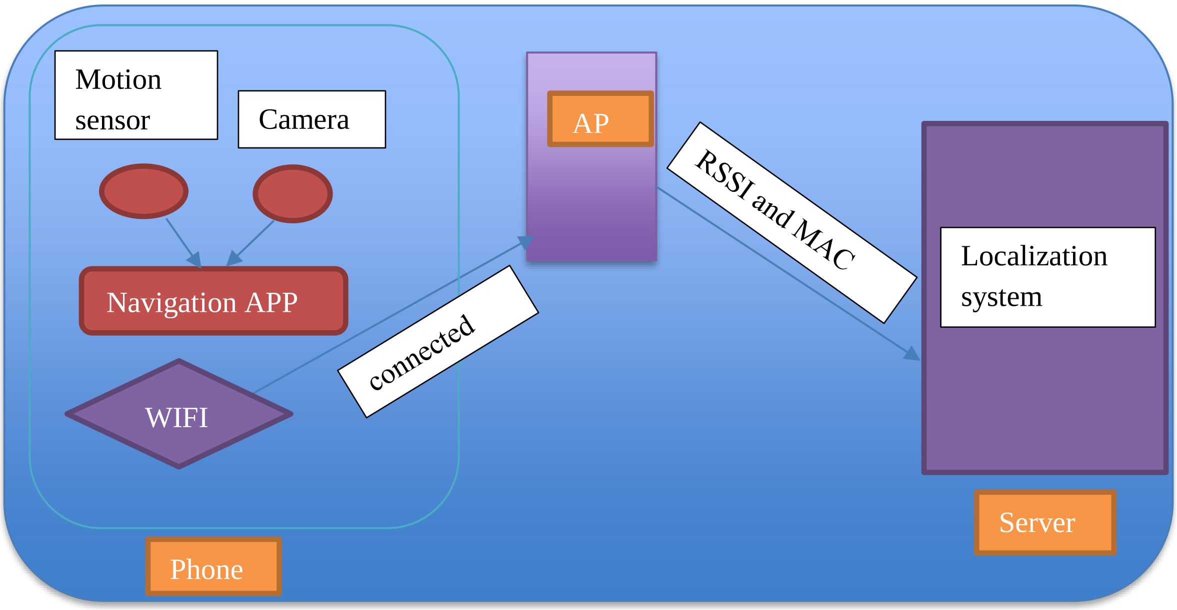

Figure 16 – framework for indoor localization UiT Narvik campus

6. Indoor localization for industrial applications

In the previous parts, this article talked about context-awareness based service, location base service and then point out the importance of indoor localization due the fact that most human activities are done under indoor environment. The main part of this article was focus on the structure of indoor localization technology and how to design indoor localization system. What is the value of indoor localization for industry area?

The success of the modern industry is result of cooperation between human, machinery and equipment. With the rapid growing of industry scale, manufacturing Information and Communication Technology(ICT) is playing an increasingly importance role which help the big and Small and Medium Enterprises(SMEs) to optimize the management performance. However, due the fact that these current ICT solutions lack the ability to provide the accurate information to the right person, the ICT is already a challenge for mangers now[126]. It is urgent to implement these ICT platforms with context-awareness ability[127].

6.1 Work activity management

When the manage can know the location of workers in real-time or the system can record the trajectory of workers related to the time information. The manager can give instructions too right person according their current location. Trajectory recording system can assure that workers or patrolman does their job properly. This is extremely important when it relate to daily factory infrastructure inspection or security patrolling.

Peng Lin[128] used his system to monitor the real-time behavior for large-dam construction site in order to have better documentation, analysis and understanding of the worker performance and improve the poor practices. To achieve this goal, the system predefined the trajectory worker are supposed to follow, then the real-time position of workers is monitored and recorded so that it can draw a real trajectory. By comparing these two trajectories by Euclidean distance, dynamic time warping (DTW), or longest common subsequence (LCSS), the behavior analysis can be done. The collected data can be sent to industrial engineers to improve the performance and can be used by HR (human resource) as a reference to evaluate the work behavior of every individual worker.

6.2 Risk management and emergency rescue

Security is a vital issue for all the industrial activities. Indoor localization can help to manage the risk and rescue when disaster happened.

In an indoor localization system, risk sensitive area can be marked, when the system detect anyone except maintenance related employee get close to theses areas, the system can alarm the approaching person and the manager when it is necessary. When a worker detected new risk situation, the worker can help to update the system. So the system can alarm other colleagues.

When a accident happed, it can be hard for rescue crew to find injured person. They don’t know how many people are trapped and where they are. Indoor localization system can give this information when the system is still working, or give the last position of workers when related infrastructure are broken. This information can help the emergency team to save people in a much efficient and confident way.

Peng Lin in his later work in [7] developed an indoor localization system with artificial neural network(ANN) risk assessment function in order to improve the safety management for tunnels workers. In this system, real-time position of workers with smartphones is monitored. They can report and share real-time risk information and be alarmed when they were approaching a risk area. The company can build and maintenance risk issues management system based on the reported information.

6.3 Factory maintenance

The scales of factories are growing in a rapid speed the layout of the site is updating frequently. With the help of wireless network sensors and system, devices position is much more flexible than ever. On one hand, this gives huge benefits for industry development, however on the other hand, this gives maintenance work extraordinary challenges. Nowadays, factories are equipped with advanced machines which need professional maintenance from external service provider or machine supplier[129]. It is important to reduce the time for engineers to navigate himself to the device.

Dipl in his work[130], detailly explained that the spatial context information can significantly optimize the maintenance process in the modern *SmartFactory*. The indoor navigation service help the engineer to find the target device in a rapid and efficient way and enhanced the quality of services and process. This can lead to a better device reachability and overall equipment effectiveness.

7. Further work

7.1 Build a system

This article is mainly to systematically introduce every side of indoor localization. This is for those who are interested in indoor localization technology but suffer from drowning in the articles that focuses on special side or sides about this topic. Almost every section of this article can be chosen as a future research area, however the combination of different sections can be hundreds of possibilities. That is what we can see in the current thousands of research works.

However, due to the limit of time. A system could not be built to apply the knowledge this article studied before. Building a system not only requires the design principles and indoor localization knowledges, it requires hardware system building and software design, testing and debugging. For example Jure Tuta et al[8] published their work after two-year-long team research, Xiong [61] finished his doctor degree research by achieving AOA based indoor localization with the special hardware with multiple antennas.

I have already contacted with some companies, which have research and application of indoor localization, in china. Hopefully I could build real life indoor localization system with them.

7.2 Analysis and improve the system

The research work can be done by three steps: 1) study current achievement; 2) build a system; 3) improve the system. This article is only the first step. And 7.1 will be the second. As we have talked about system evaluation and improvement algorithms. I want to apply them in the real-life environment instead of experimental setups. In the future project, I will decide the device and approaches after analyzing the real-life situation and apply algorithms and topologies to reach the requirements of needs.

7.3 Implement the system design part

In this article, I wanted to introduce the design principle for indoor localization, which is so far from my knowledge no one ever did this work before. There is only one article I found in our data base from Jorge Juan Robles in his “Considerations in the Design of Indoor Localization Systems for Wireless Sensor Networks”[131], but this article just gave some little aspect of indoor localization system design for example, energy consumption and protocol introduction. It does not contain principles, devices and other approaches.

But my experience and knowledge is limited, this topic is still just a start of all. Hope more researcher would like to give their implements to give more comprehensive, abstract and complete design procedures in the future work.

In operation research, one of the important subject in industrial engineering, talked about decision analysis. In the future work, I would like to implement this into system design part also. Hope there can be better designs.

8. Conclusion

This is an article talking about wireless indoor localization and applications. Here wireless does not only mean WIFI, Bluetooth, ZigBee, wireless HART and other RF signals, it also contains sound waves, light signals. It tried to give a systematical, structural description of indoor localization. It is a survey and it is also not only a survey, as far as the author knows, there is not a single article which contains so many aspects of indoor localization. Talking about indoor localization technology, there is not a single article which talk about it so completely. Of course, indoor localization is not a complete system yet. Only limited start-up companies trying to concur this market. This subject is only a little branch of electrical engineering or mathematic subject. There is not text book available yet talking about this area. That is a limit for more passionate students coming to contribute their intelligence and hard work. This article can be a beginning of this kind of book.

This article systematically described the basic techniques of indoor localization. Chapter 3 give the basic technological knowledge of indoor localization. This part is concluded from over hundreds articles from the database. After reading this part, the reader can have a better understanding of future articles. They can know which area of indoor localization the future article is doing. They can also know what they can use they want to build their own indoor localization system or make their own contribution in indoor localization work.

Chapter 4 is smart phone based indoor localization. This part is based on the opinion that smartphone is the common device everyone takes with all the time. Therefore, smartphone is the most potential platform and most possible way to build indoor localization system. All the sensors available inside the modern smartphone are listed and how every sensor can be used for indoor localization applications are introduced separately in the beginning. In the end, fusion solutions are talked.

Chapter 5 talked about designing of indoor localization. This topic never been talked before, thanks to the work in chapter 3 and chapter 4, this topic can be started based on the systematical knowledge. In the end, some famous algorithms are added. Due to my limit knowledge, there can be some missing algorithms. I would like to add them in my future work.

Chapter 6 talked about industrial applications of indoor localization. Some current applications are introduced.

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