CHAPTER 2

Overview of Positioning Technologies

The exponential growth of usage of mobiles as hand-held devices demands innovative applications such as location-tracking (Haeberlen et al., 2004). Determination of the position of a mobile device has many useful applications such as navigation, tracking of minors or other individuals, and/or other LBS offered through a wide area mobile communication network. Location tracking of a device can be accomplished for both in indoor as well as in open air conditions. The accuracy of the tracking is the principle dispute especially when the mobile device is moving (Paul and Wan, 2009). Diverse dimensions of accuracy are acquired for various applications. The extensively accessible procedure is GPS where, it offer solutions with exceptional accuracy for open air/outdoor applications. But for indoor conditions, yet it isn’t appropriate (Ali et al., 2004; Haeberlen et al., 2004).

With advances in sensor technologies, alternative positioning systems such as using RFID, Infrared Radiation (IR) and because of their specific characteristics, radio advances like Ultra Wide Band (UWB), Zigbee, Bluetooth, Wi-Fi are useful for indoor positioning. Techniques like Wi-Fi have gained increased popularity though it has some challenges.

This chapter is structured as pursues: Section 2.1 acquaint Indoor Localization Determination methods and techniques. This is applicable for both indoor and outdoor. Section 2.2 discusses about various performance metrics. Section 2.3 is devoted for typical systems and solutions. New developments in IPS are discussed in Section 2.4 and in Section 2.5 Conclusions are presented.

2.1 Methods and Techniques for Localization Determination

The real time estimation of one of distinct parameters like angles and distances/distance differences decides the capability of the localization techniques (Hightower and Borriello, 2001). The estimation of these criterion mirrors the area of a target device with connected to a solitary point or a few fixed focuses in the ambiance with the familiar locations. The estimation of these criteria is by utilizing the physical qualities of signals like their movement time, speed and so on. There are three methods and techniques for
location calculation and estimation as shown in Fig 2.1.

![Location Detection Systems Diagram](image)

**Fig. 2.1** Classification of location tracking systems

Each of these has unique advantages and drawbacks so using more than one algorithm may improve the performance (Liu et al., 2007).

2.1.1 Proximity Algorithms

These depend on the closeness of the cell phones to recently known areas. Consequently, proximity detection will provide the relative coordinates of the targets; hence, these are also called coarse-grained methods. Nearness to a given Wi-Fi AP bounds the client’s location to a vast and complex area. A typical adaptation is, to assume that a circle with radius ‘r’ would represent the scope of wireless infrastructure then, the proximity restraint within the circle. For several circles, the possible location can be limited to the intersection of the different circles like a model shown in Fig 2.2.

![Proximity Detection Diagram](image)

**Fig. 2.2** Illustration for proximity detection
In another method, dense grids of antennas are used for tracking. If a single antenna detects the target, the information is collected from it, and if multiple antennas discover it, then, the antenna with the most powerful signal is utilized. These can be implemented by methods like IR or RFID.

2.1.2 Triangulation

In this strategy, the location of the gadget will be determined by applying basic trigonometry. There are two forms in this strategy: one is, lateration and the other is, angulation.

The physical place of the gadgets are determined in Lateration / Trilateration / Multi lateration by estimating their separations from various reference focuses. Hence these are all also referred as distance or ranging method. In trilateration, the term “tri” indicates at least three fixed reference points are required for estimation (Zahid et al., 2013). In lateration, tracking techniques are based on TOA, TDOA, RSS and received signal phase techniques (Ismail et al., 2008; Zhang et al., 2010).

The time of arrival calculation from the transmitter to the receiver is used in TOA/Time of Flight (TOF) technique. In this methodology, numerous transmitters transmit signals to the recipient as appeared in Fig 2.3. Upon receiving, at the receiver, the time of arrival of all the signals are calculated and compared. Then the distance between the mobile targets to the measurement system is related to the propagation time. But the main requirement of this method is that, it requires all the transmitters to be precisely synchronized with the receiver system.

As the multipath effects are filtered out in TOA, it is considered as the most accurate method for indoor applications (Gu et al., 2009).
An improved version of TOA is TDOA where, it does not require synchronized
time source of transmission and also it is free from packet loss problems (Nájar and
Vidal, 2001). Here the sender should send two distinct signals with various proliferation
speeds and at the reception, the contrasts between the arrival time are estimated and it
is actually coordinating with the spread time of a signal. TDOA based location tracking
is an example of multi lateration (Zahid et al., 2013).

If two base stations, the distinctions seperation from mobile phone to the base sta-
tion as a known value of $\nabla d$ at that point, the phone stay on the hyperbolic bend characterized by this separation as portrayed in Fig 2.4.

![Fig. 2.4 TDOA based positioning](image)

In order to position the mobile device, the following equation is established with
constraining the gadget’s location on the hyperbola characterized from the estimations:

$$\nabla d_{ij} = \sqrt{(m_i - m)^2 + (n_i - n)^2} - \sqrt{(m_j - m)^2 + (n_j - n)^2}; \ i, j = 1 \ldots k, i < j$$

(2.1)

Where, $(m_i, n_i)$ and $(m_j, n_j)$ denotes established receivers $i$ and $j$. The coordinate
of the object is defined by $(m, n)$. It is more often than not to incorporate the distance estimations regarding one established station like; $i = 1$. The definite answers for the
Eqn.2.1 are by applying nonlinear regression and Taylor expansion.

Another technique where, the object position is reckoned by limiting aggregate of
squares nonlinear cost work is, the least square algorithm (Fang, 1990; Kanaan and
Pahlavan, 2004; Liu et al., 2007). Let the node be situated at $(m_0, n_0)$ which transmit
a signal at moment $t_0$, and there are $N$ stations situated at $(m_1, n_1), (m_2, n_2), \ldots, (m_N, n_N)$ are able to get the signs at time $t_1, t_2, \ldots, t_N$ then, the cost function can be shaped by the Eqn.2.2 (Liu et al., 2007).
\[ C(m) = \sum_{i=1}^{N} \alpha_i^2 c_i^2(m) \] (2.2)

Where, \( \alpha_i \) is the chosen parameter which reflects the reliability of the signal received and \( c_i(m) \) is given as,

\[ c_i(m) = v(t_i - t) - \sqrt{(m_i - m)^2 + (n_i - n)^2} \] (2.3)

Where, \( v \) denotes the velocity of the light, and \( m = (m, n, t)^T \). By carefully selecting the values of \( m, n \) and \( t \), the term \( c_i(m) \) in Eqn.2.3 can be made zero. The location is estimated by minimizing the cost function \( C(m) \) in Eqn.2.2.

The trip time of the signal is measured between the transmitter to the unit of measurement and back in the Round - Trip Time of Flight (RTOF)/Round Trip Time (RTT) technique. Contrasted with TOA, RTT utilizes just a single node to report the sending and entry times. Due to this, the synchronization issue is unraveled to some degree. However, one of the primary concern of this procedure is, for distance estimations to numerous gadgets that should be done at the same time give rise to insecure delays (Zahid et al., 2013). The same positioning algorithms can be used for both RTOF and TOA.

The phase differences of the acquired signals are utilized in the received signal phase technique to calculate the distance. In the event that, all the transmitters emanates sinusoidal wave with identical frequency, then the receiver requires a transit delay to find the phase of the acquired signals (Liu et al., 2007).

In Fig 2.5, it is assumed that, there are four transmitters \( P, Q, R \) and \( S \), placed at the corners of a cubic space. The delay is denoted by wave length of the signal.
\[ \theta_i = \frac{(2\pi f R_i)}{v} \] in equation, \( S_i(t) = \sin(2\pi ft + \theta_i) \), where \( v \) represents speed of light and \( i \in \{P, Q, R, S\} \). We can get the range estimation \( R_i = \frac{(v\theta_i)}{(2\pi f)} \). Then, the same positioning algorithms adopted in TOA measurement can be used.

In AOA computation, the position of an objective is measured by the convergence of various sets of AOA of the mobile signals from a base station or beacon station. In two dimension plane, it requires two beacons to determine the target. In order to improve the accuracy, it requires three or more beacons for location estimation.

![Fig. 2.6 AOA position method (Liu et al., 2007)](image)

In Fig 2.6, let \( X, Y \) are two reference points (base stations) and two measured angles, \( \theta_1 \) and \( \theta_2 \) are used to find the target \( P \). The advantage of AOA is, no time synchronization between measuring units is needed. But the drawback is, the estimation of AOA requires either directional antenna or an array of antennae. Also the performance degrades when the objective is portable and moves far from the estimating units.

### 2.1.3 Scene Analysis

In this, initially fingerprint of a scene is collected and then by matching with the online measurements, an object will be located. Hence these are also called as fingerprinting methods. This method is quite popular in positioning problems due its low cost deployment, simple and better accuracy compared to other techniques. But in the indoor environment, as the signal strength is affected by different factors like diffraction, scattering and reflections, positioning is challenging.

The location (or unique position) is represented by using the RF characteristics such as RSS. It depends on the suspicion that every spot within the structure has an exclusive mark (Pahlavan et al., 2002). For the most part, the unique finger impression “F” is
named with an area “L”. The area fingerprints and their names are kept up in database and utilized amid the on-line stage to assess the area.

The location data can be documented in two structures: as either a tuple of directions or a pointer variable (Battiti et al., 2002). Here the tuple of real genuine directions are fluctuate upon one to five proportions. For example, in two dimension framework, the orientation could be communicated as a triplet \( L = \{(a, b, d) | a, b \in \mathbb{R}^2, \ d \in \{\text{North}, \text{South}, \text{East}, \text{West}\}\} \). The pointer variable reports just the article is inside or outside the zone. For instance, Battiti et al. (2002) mentioned in their work for \( L \) as \( \{-1, 1\} \).

The promptly accessible RF in every WLAN interrelatedness permits the RSS as the straightforward and ideally utilized strategy for area fingerprinting. As the noise component is irregular in nature, compared to Signal to Noise Ratio(SNR), the RSS is location reliant (Bahl and Padmanabhan, 2000). But for each AP and location, the RSS itself fluctuates over time. In a given area, the fingerprint information is generally indicated by random variables/vectors which denotes received signal strength from that area. For every spot, more tests of vectors of sign energy are gathered over a given time and this premise is known as a model (Tou and Gonzalez, 1974). Subsequent the normal RSS of every AP is determined and reported as a component in the area fingerprint (Kaemarungsi, 2005).

In another methodology, the likelihood dispersion is assessed for the RSS impression at a specified area (Battiti et al., 2002; Ladd et al., 2002). Then location estimation is done by using Bayes rule. Further discussion about Bayes algorithm are given in the next subsection as well as in next chapter.

Deterministic methodology and probabilistic methodology are the two different ways that are utilized to show the connection between the RSS stamp and the area data. In the primary methodology, the location data is attached to the consistent estimation of normal RSS vector though in the second strategy it abuses the probabilistic reliance (Kaemarungsi, 2005). Aside from the premise location finger impression, estimating tests amid the on-line stage is critical if, that the framework tracks the portable item.

A stage in factual investigation strategy called preprocessing is another critical issue should have been considered in light of the fact that it can affect the estimation of reliance between area fingerprint and the area data (Pardo and Sberveglieri, 2002). Here the preprocessing alludes to a stage that cleans the crude data(for the preparation set) prior to any further examination. The cleaning comprise of decrease of pointless components, encoding, anomaly end (Saha et al., 2003) and clustering (Pardo and Sberveglieri, 2002). According to Roos et al. (2002), the preprocessing not only enables the speedy location estimation but also it reduces the noise from the training data.

Positioning algorithms or area estimation calculations are methods that take advantage of dependency between the area data and fingerprint premise so as to decide a
position from the RSS signals specimens.

The two prevalent models accessible for location assessment are: the robust base station and arbitrary choice methods. In the first method, the selection technique expect that the present client’s position is nearer to the base station and while the second technique reporting the client’s situation indiscriminately set of known locations (Bahl and Padmanabhan, 2000; Kaemarungsi, 2005). But the fact is that, these two algorithms performances are not giving agreeable outcomes. Complex calculations which exploit the reliance between the RSS finger impression and area data could give the better precision of the location data. The significant calculations are talked about beneath.

The first one is, Nearest Neighbour Methods (NNM). These are deterministic algorithms which demand vectors of mean and normal divergence of RSS. NNM are also termed as case based strategies as it group every position in to a case/class (Roos et al., 2002).

The fundamental calculation of NNM chooses the magnificence or case dependent on the affinity of an example fingerprint regarding the center of the mass of that specific area fingerprint.

Let a lot of $l$ area fingerprints be signified by \{f$_1$, f$_2$, ..., f$_l$\} occur and all has a coordinated mapping to set of spot \{l$_1$, l$_2$, ..., l$_l$\}. Amid on-line phase, the estimated RSS fingerprint test is indicated as $C$ which may be additional mean or normal RSS vector of a minimum window of tests.

Expecting that, an IPS just contemplate the normal RSS from $N$ AP’s as an area fingerprint, the example of RSS vector is $C = (C_1; C_2; ;; C_N)^T$ (Kaemarungsi, 2005). Every area finger impression $i$ in the data index can be indicated as $f_i = (\rho_i^1, \rho_i^2, ... \rho_i^N)^T$.

Distance measurement in signal space is represented by a simple metric function $D(.)$ (Saha et al., 2003). Along these lines, the basic methodology of NNM is indicated as, choosing the finger impression $j$ which has the briefest signal seperate as given in Eqn.2.4

$$D(C, f_j) \leq D(C, f_k), \forall k \neq j$$ (2.4)

By using additional information of standard deviation fingerprint, a modification of NNM was studied by Saha et al. (2003). At the point when an example finger impression be situated outward the field of two general deviations on all sides of a mean RSS, then it can be expected that a pattern may not be correlated with any position in the data base. This special class of NNM is called as non-classifiable pattern. In this modified approach, the distance estimation accuracy is more (Saha et al., 2003).

$k$-Nearest-Neighbour (kNN) is one more strategy that utilizes the online RSS to seek $k$ nearest equals of familiar areas from the officially inherent information base agreeing to RMS error standard (Liu et al., 2007). Weighted kNN and un weighted
kNN are the two classifications of kNN where the difference is, whether the weights of the \( k \) locations are used with or without accommodating the signal space. Here \( k \) is the selected criterion and if its value greater than eight then, the performances become worse (Prasithsangaree et al., 2002).

The second kind is, based on Neural Networks. This sort of IPS assumes that, the finger impressions are too intricate to be in any way dissected numerically and it might require unobtrusive non-direct discriminant functions for characterization (Kaemarungsi, 2005). So all things being equal of finding reasonable discriminant capacities. For example, for the minimal distance metric, this methodology uses a summed up structure called neuron (Kaemarungsi, 2005; Saha et al., 2003).

The neuron comprises of a lot of info joins weighted with synapse loads, pursued by a summator that aggregates every single weighted info and lastly an enactment function that restrains the adequacy of the yield of the neuron (Saha et al., 2003). The enactment function is for the most part in a type of non-direct function, for example, a sigmoid function (Battiti et al., 2002; Kaemarungsi, 2005).

Battiti et al. (2002) proposed Multi-Layer Perception (MLP) neural network where in this, they have interconnected various neurons both in sequential and parallel. In these neurons, the signals move gradually from the first layer to the last layer in addition to output of one to the contribution of other neuron. All the other layers amidst the first and the last are termed as hidden layers. The RSS from three AP’s are considered as inputs of three features.

Samples of labeled area fingerprints are used to ascertain every synaptic loads within the neurons in every neural system of MLP (Kaemarungsi, 2005). There are two algorithms proposed for finding synaptic weights and they are One-Step-Secant (OSS) algorithm (Battiti et al., 2002) and error back propagation algorithm used by Saha et al. (2003). In these, in OSS, it iteratively adjusts all synaptic weights with second derivative information. These training techniques consequently make complicated limits of region fingerprint groups (Kaemarungsi, 2005).

The MLP neural network model does not require any environment parameters like path loss component and the location of APs (Battiti et al., 2002). When comparing to NNM in MLP, the accuracy and precision parameters are reported better but not very significant (Battiti et al., 2002; Saha et al., 2003). For example accuracy in MLP was 1.82\( m \) compared to 1.81\( m \) for kNN.

Slow training and requirement of large training set are the drawbacks of neural networks. Additionally the failure execution of neural systems can’t be determined logically because of its multifaceted nature. Sometimes, over training or over fitting will also lead to poor location estimation. This usually occurs when the number of iterations is more than 3000.

Though the neural network method seems to be different from NNM from statistical
point of view, but it also creates decision boundaries like NNM. Also the neural network methods provides rare insight information on the underlying mechanism of IPS. The third classification is, Support Vector Machine Methods (SVMs). It is a new technique which can be used for both classification and regression challenges. It is widely utilized for variety of utilizations like engineering, medicine etc. (Correal et al., 2003; Li et al., 2000).

SVMs have their roots in statistical learning theory. For example, the algorithm proposed by Vapnik (1998) combines the techniques like statistics, machine learning and neural networks. When comparing with the probabilistic method, this approach does not require any definite properties like proliferation model to evaluate the reliance between the RSS finger impression and the area.

The principle quality of SVMs calculation relies upon its capacity to sum up characterization which limits the inaccuracy of the test for the information after the preparation time frame (Kaemarungsi, 2005). As such from the little preparing set, by correctly preparing the the learning machine, the structure for arrangement can be made as memory less (Battiti et al., 2002; Kaemarungsi, 2005).

The SVMs calculation depends on Structural Risk Minimization (SRM) guideline where, the SRM attempts to limit the constrained on risk function error (Battiti et al., 2002; Kaemarungsi, 2005). It denotes, an anticipated price of a loss function wherein, loss characteristic denotes a degree of variations between the feature used to surmised the sample mapping from the actual sample mapping. The risk function is limited by Vapnik-Chervonenkis (VC) confidence interim.

The characterization functioning operations of SVMs are started by performing vector transformation with the help of utilizing a function of the SVM Kernel. It is done by the mapping of the vectors of location fingerprints into higher dimensional space called future space (Battiti et al., 2002). In that, the SVMs calculation makes an ideal isolating hyper plane (or choice space) and uses it to perform grouping.

Despite the fact that, the SVMs are novel and successfully used in pattern recognition but usage of this for IPS problems does not show much improvement in performances as compared to other techniques. For example, in regression problems like in weighted kNN, the error distance is $3.93m$ at 75% whereas in SVMs, it is $3.96m$ at 75% (Battiti et al., 2002). The SVMs calculation is appropriate to decide whether, the location is inner or outer the closed environment and these are cases of classification problems. In the previous three methods, the success of the positioning framework relies on mean square error and in SVMs it relies on acceptance error (Jain et al., 2000). Since many kernel functions are accessible to look over, the classifier execution can be improved by proper selection of a kernel of SVMs and its parameters. From the hypothetical displaying point of view of this examination, it is observed that for positioning problems, the SVMs are more complicated on providing the required data.
Smallest M-vertex Polygon (SMP) is the next in classification. It utilizes online RSS data to look object positions accompanying every transmitter independently. In case if M transmitters are used, then from each transmitter one candidate is chosen and M-vertex polygons are formed. Then the area estimation is done by using the numerical mean of directions of vertices (Prasithsangaree et al., 2002).

The final method is, based on Probabilistic Methods. In this strategy, Bayesian inference is used for the area estimation which intern uses fingerprint information with contingent probability (Ladd et al., 2002; Roos et al., 2002; Youssef et al., 2003). In this methodology, the earlier information about the probability density of client’s area is used and due to this, it gives a better estimation than NNM (Kaemarungsi, 2005; Youssef et al., 2003). The a priori location distribution is maintained as additional information of personalized user location profile by the IPS and this can improve in the application of location tracking (Ladd et al., 2002; Roos et al., 2002).

Let the area coordinate is denoted as \( L \) then, from the pattern of training set of fingerprints, the conditional probability density function is calculated as \( P(F|L) \). In order to estimate the likelihood function, Roos et al. (2002) suggested two strategies: the kernel method and the histogram method. In the first technique, from available n RSS pattern from an AP in an area of one dimensional precedent, the kernel method forces a likelihood mass (Gaussian appropriation) on every values of RSS pattern. The mean value of one of n RSS pattern is denoted by \( \rho \) and standard deviation \( \sigma \) denotes discretionary alterable kernel width (Kaemarungsi, 2005). For the given area \( L \), the subsequent probability capacity of RSS tests are given with the aid of similarly weighted total of all \( n \) Gaussian kernel capacity and it is given as (Kaemarungsi, 2005),

\[
P(C/L) = \frac{1}{n} \sum_{i=1}^{n} \left[ \frac{1}{2\pi} \exp \left( -\frac{(c - \rho)^2}{2\sigma^2} \right) \right]
\]  

(2.5)\

Roos et al. (2002) extended this kernel method for multiple dimensions or in multiple APs,

\[
P(F/L) = P(C_1/L)P(C_2/L)\ldots P(C_N/L)
\]  

(2.6)\

In the above Eqn.2.6, the authors have made assumption that all conditional probabilities are independent.

In the histogram method, by using discretized density functions, the continuous density functions are estimated. It tallies the appearance frequency of RSS tests on an established set of bins. The flexible number of receptacles and the known estimations of least also, greatest RSS values are utilized for ascertaining the range.
2.2 Performance Metrics

Based on the application of positioning, there are different metrics used in various approaches like cost, accuracy; technology etc. (Huang and Gartner, 2009; Liu et al., 2007; Mautz, 2012). For example in the case of indoor navigation for blind applications, accuracy is used. In this section, we discuss different performance metrics of IPS.

2.2.1 Accuracy

It denotes the distance mismatch between the predicted location to the existing location of the mobile device. In spite of the fact that, it is an essential measurement for some applications, a few bargains may be acknowledged among precision and different measurements (Liu et al., 2007; Mautz, 2012).

2.2.2 Coverage

It is the scope of space the positioning system covers. It is obvious that, the most effective system is one, which covers wider area (Chen et al., 2014). This metric is classified into local, scalable and global based on the area it covers (Mautz, 2012). If the area is limited like a small room then it refers local. Here, the coverage area is stated. Frameworks with the capacity of expanding the region of inclusion by including equipment/hardware is termed as scalable area. If the inclusion region is of bigger size like around the world than it alludes global coverage (Liu et al., 2007). Now a days, the existing IPS coverage varies from $5m$ to $50m$ (Al-Ammar et al., 2014). Hence providing coverage for more than $60m$ is challenging (Chen et al., 2014).

2.2.3 Scalability

It is the desirable property which suggests that, how good the system performs during large number of location requests and a larger coverage area. A versatile positioning framework ought to have the capacity to deal with substantial quantities of solicitations without great deal of strain (Liu et al., 2007). Poor scalability will lead to performance declining which is undesirable and requires re-engineering the system.

2.2.4 Adaptiveness

As the performance of the system is influenced by environmental factors, it is desirable for the localization system to adapt with the changes. Systems unable to cope with the changes will lead to deliver poor performance. An Adaptive system also does not need repeated calibration (Liu et al., 2007).
2.2.5 Cost

Cost parameter is measured in various ways: money, cost of extra infrastructure, additional bandwidth requirement and nature of technology used in the system. The cost parameter also includes installation cost. Sometimes the system may reuse some part of the existing infrastructure such as equipment, bandwidth and communication infrastructure, and in these cases the system may be cost effective (Liu et al., 2007).

2.2.6 Energy

Energy may be a critical resource to avoid disruptions in service. The positioning devices vary based on the energy consumption. In the case of RFID based system, the passive tags are energy passive and whereas the active tags are packed with internal power sources and will eventually require replacing (Al-Ammar et al., 2014).

2.2.7 Availability

It alludes the portion of time the framework is accessible for use with necessary precision. There are factors such as communication interference, maintenance etc., which influences the availability of the system with desired performance. Chen et al. (2014) showed that, based on the availability, the framework might be distinguished as low accessibility ($< 95\%$), normal accessibility ($> 99\%$) and high accessibility ($> 99.9\%$).

2.3 Typical Systems and Solutions

Wireless positioning solutions of a node are offered both in outdoor and indoor environments. The important differences between these environments on offering the solutions are highlighted in Table 2.1

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Indoor</th>
<th>Outdoor</th>
</tr>
</thead>
<tbody>
<tr>
<td>Path Loss Model</td>
<td>Influenced by shadowing and multi path</td>
<td>Narrow</td>
</tr>
<tr>
<td>Accuracy</td>
<td>Hard to accomplish (since limited area)</td>
<td>Simple to accomplish (Due to more extensive space)</td>
</tr>
<tr>
<td>Deployment</td>
<td>Can be Prepared</td>
<td>Arbitrary</td>
</tr>
<tr>
<td>Transmission Power</td>
<td>Adjustable</td>
<td>Maximum required for ensuring quality</td>
</tr>
<tr>
<td>Height of reference</td>
<td>Ceiling</td>
<td>Ground</td>
</tr>
<tr>
<td>Mapping Area</td>
<td>Local</td>
<td>Global</td>
</tr>
</tbody>
</table>

Table 2.1 Correlation of indoor and outdoor conditions (Pu, C. 2011)
This section presents overview of some of the prominent wireless positioning systems. The main focus is radio based systems in positioning problems for indoor applications.

2.3.1 GPS

In outdoor environments, one of the most prevalent techniques in locating the region or situating an item or gadget is by using either GPS or its differential supplement (DGPS) (Enge, 1994). But for indoor locations, it shows less accuracy. It is mainly due to presence of the obstacles (like walls, partitions in buildings) in the LOS between satellite and the object (or device).

2.3.2 RFID

This is another useful and promising technology for locating the people or devices. The basic components in the system include readers and tags. It enables one way non-contact wireless communication between the reader and tags. There is a well-defined RF and protocol in RFID for both, transmission and reception. There are active and passive tags. The difference is that, the passive tags are smaller in size, cheap, weightless and do not require a battery for operations. It operates at variety of frequencies like 125KHz, 13.56MHz for low and high ranges respectively and also at ultra-high (433, 868 – 915MHz) and microwave frequencies (2.45GHz, 5.8GHz) (Liu et al., 2007). The typical operating range of passive tags is varying from 1m to 2m.

As the active tags are comes with smaller antenna, they are useful for long range (tens of meters). SpotON is the well-known RFID technology for location sensing systems where here, the received RSS value can be used for estimating the tag distance (Hightower et al., 2000).

2.3.3 UWB

It is known for short range high bandwidth communication (Zahid et al., 2013). When comparing to RFID, the UWB operates on multi band of frequencies from 3.1GHz to 10.6GHz (Gezici et al., 2005). Power consumption is also less in UWB than RFID. As the hardware is costly, the UWB based system are used in applications that require accuracy of 20cm – 30cm.

UWB is depends on transmitting brief term beats (< 1ns) over a small duty cycle of 1 : 1000. To distinguish correct signals from the reflected signals, these pulses are simple to filter. These are additionally helpful for flawless calculation of the TOA and TOF among an emitter and to a collector (Fontana, 2004; Gezici et al., 2005). For 3-D positioning, measurements from both TDOA and AOA are used and due to this, it combines advantages of both the systems.
2.3.4 WLAN / Wi-Fi

These systems are quite popular as these are compatible (not requiring any software installations and other stuffs), scalable and do not require LOS (Mak and Furukawa, 2006). The other fascination is, the framework do not need any equipment to quantify the values of signal strength. That is to say, signals from the existing Network Interface Cards (NICs) in hand held computing devices are used for positioning. Many research works are available on Indoor localization using Wi-Fi (Table 2.2).

<table>
<thead>
<tr>
<th>Work</th>
<th>Positioning Algorithm</th>
<th>Accuracy</th>
<th>Remarks</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bahl and Padmanabhan 2000</td>
<td>kNN</td>
<td>$2.37 - 2.65m$</td>
<td>Wall Attenuation Factor; Floor Attenuation Factor are considered.</td>
</tr>
<tr>
<td>Prasithsangaree et al. 2002</td>
<td>SMP</td>
<td>$2.7m$</td>
<td>$50%$ of time accuracy within $2.7m$</td>
</tr>
<tr>
<td>Roos et al. 2002</td>
<td>Bayesian approach</td>
<td>$1.5m$ (More than $50%$ of time)</td>
<td>Location estimation accuracy of less than $2m$ was achieved by using probabilistic model approach.</td>
</tr>
<tr>
<td>Battiti et al. 2002</td>
<td>SVM</td>
<td>$3m$</td>
<td>For 5 samples the error is $3m$. With more samples the error reduces to $1.5m$.</td>
</tr>
<tr>
<td>Ladd et al. 2002</td>
<td>Bayesian Robot Localization</td>
<td>$1.5m$ ($83%$ of time)</td>
<td>Two phases involved in locating the host. In first phase with fixed host, RSS from 9APs are measured. In the second phase, the result is refined by keeping the host in motion.</td>
</tr>
<tr>
<td>Youssef et al. 2003</td>
<td>Probabilistic Method</td>
<td>within $2.1m$</td>
<td>Accuracy increases with more samples.</td>
</tr>
</tbody>
</table>

2.3.5 Bluetooth

It is a wireless paradigm that works in the ISM band of $2.4\text{GHz}$. Since it holds many advantages like low power consumption, cost effective, highly secured and optimum in size, enabling it use for positioning. But these devices will take some time for discovering the devices for each time location finding, it increases the localization latency to $10 - 30 \text{ seconds}$ (Zahid et al., 2013). Bluetooth based Local Positioning Application (BLPA) was presented by Kotanen et al. (2003).

2.3.6 Zigbee

Zigbee devices are known for their low power consumption and not requiring large data throughput.
These are useful for short and medium range communications from 20m to 30m (http://www.zigbee.org/About/AboutTechnology/ZigBeeTechnology.aspx, 2013). The distance estimations are done by using RSSI values and it operates in the unlicensed ISM band. The notable work using Zigbee for localization is reported in Fang et al., (2012). They have used ad hoc Zigbee network for indoor localization.

2.3.7 Others

Frequency Modulation (FM) is another popular method. IPS based on FM radio signs was conferred in (Moghtadaiee et al., 2011; Popleteev et al., 2012). Hybrid Positioning Systems (HPS) are working by combining many positioning technologies to locate a device (Mehmood and Tripathi, 2011; Zirazi et al., 2012). Since GPS doesn’t function well admirably in indoor situations and the methods used in indoor locations are less precise in the open air, the concept of HPS is proposed where, it works well for both indoor and outdoor localization problems. Some of the popular examples for HPS are, Combain Mobile, Navizon, SkyHook, Xtify, and Google Maps for Mobile (Zahid et al., 2013).

The location frameworks based on Ultra-High Frequency (UHF) work either in the 433MHz band or on the 868MHz and 2.4GHz ISM band (Liu et al., 2007). At these frequency ranges, obstacles like walls have a moderate attenuation. Where Net is an example for TDOA frame work in 2.4GHz (Werb and Lanzl, 1998). IR is one more prominent wireless method utilized in Wireless Personal Area Network(WPAN). The vast majority of wireless framework of the Infrared Data Association (IrDA) are LOS basis (Liu et al., 2007). The combinations of highly available UHF and accurate IR methods results in to hybrid location detection system (Want et al., 1992).

In ultrasound frameworks, the ultrasound signals are utilized to evaluate the location of the transmitter tags from the collectors (Zahid et al., 2013). Ultrasound based Indoor positioning is carried out in (Medina et al., 2012; Runge et al., 2011). As ultrasounds are not able to penetrate walls, it has more indoor reflections and hence it is less accurate.

2.4 Review of Recent Developments in IPS

As the IPS based research is growing fast, there are many research works done over the years. But covering all these developments is not feasible. Hence in this section, few of the sample works proposed since the year 2010 are covered and finally the comparison of all the discussed techniques is given at the end (Table 2.3).

Wehrli et al. (2010) presented an IPS dependent on Frequency Modulated Continues Wave (FMCW) based radar framework. Here, a frequency ramp is transmitted by the Base Station (BS) that is echoed by a backscatter. The RTOF among the frequency transmitted and collected causes offset and this value is equal to the distance.
Cheok and Yue (2011) have developed indoor positioning and navigation framework using light sensors. Fluorescent light is utilized as the carrier for transmitting data in this work. The pulse frequency modulation procedure is utilized to encode the information. The system is portable and lightweight. The main advantages of this method is that, if the user wears this along with the wearable tracking GPS, it can also allow for tracking in outdoor environment.

Saab and Nakad (2011) studied passive RFID based IPS. The authors have implemented their work using a Kalman filter to reduce the location error. The examination is directed with interval amidst two successive tags set at $1.2m$ and the gap between the peruser direction and tag-layout direction set at $2m$. The normal outright position inaccuracy was recorded at $0.1m$.

Novel approaches of mobile-to-mobile NLOS localization scheme was given in (Chen et al., 2011). They have used proximate points and Gaussian weighting process. It has been demonstrated experimentally (with simulations) in two typical indoor and outdoor environments. They have concluded that, their proposal of 3D NLOS localization scheme outperforms the existing NLOS localization schemes in all cases in relation to various degree of TOA and AOA measurement noise.

The Zigbee based IPS with an ensemble approach was proposed by (Fang et al., 2012). This approach allows the integration of many methodologies in the course of positioning. This permits to utilize the benefits of every algorithm. Hence it is much better than the usual fingerprinting techniques.

Light Emitting Diode (LED) is used for indoor positioning. Won et al. (2013) used three LEDs in the form of triangular optical wireless zone and each allotted with location code. When the area codes are allocated to the directions of all reference focuses, their spatial appropriation map is arranged. Utilizing a calculation dependent on the spatial appropriation map, the 3D position of the item is positioned. The white LEDs based indoor positioning was discussed in (Wang et al., 2013). The proposal for IPS based on Visible Light Communication (VLC) is found in (Yasir et al., 2014). The authors have used light sensor and accelerometer equipped smart phone at receiver side to measure the received light intensity and orientation of the smartphone. The receiver position is then estimated by applying the measured values in a low complexity algorithm.

In IPS, correct placements of Wireless Access Points (WAP) are vital for better accuracy in locating a device/node. Ficco et al. (2014) presented an approach to select the best deployment schema for WAP. They have used multi-objective GA to identify the best access point placement.

Li et al. (2016) showed Feature Scaling based $k$ Nearest Neighbour (FS-kNN) IPS calculation. The trial results demonstrates that equivalent RSS contrasts at various RSS levels can be brought about by various physical separations. This additional element
has improved precision contrasted with classical kNN.

For commercial applications like pedestrian tracking, there are two popular techniques are available, one is WLAN and other is Pedestrian Dead Reckoning (PDRg). The strength of PDRg should eliminate the draw backs of WLAN and vice versa. Chen et al. (2014) proposed an intelligent algorithm which fuses a PDRg system and Wi-Fi system. It is smart on the grounds that, the underlying client area and the underlying client moving heading data are naturally inferred by the suggested techniques without needing any client contribution to progress.

In multipath phenomena, magnetic-based indoor positioning shows better performance compared to RF based solutions. De Angelis et al. (2015) designed a magnetic IPS. The proposed system allows for wide operational range and lower current consumptions. It is recommended for longer range and building wide applications.

Huang et al. (2015) developed high performance IPS based on Kalman Filter (KF). The proposal is useful in reducing RSSI drift, localization error and deployment complexity of RFID without compromising the accuracy and localization granularity.

In indoor environments, due to the hybrid LOS/NLOS, in Gaussian-based nonlinear filters such as KF or Partial Filter (PF), the measurement error is quit high. Zhao et al. (2015) characterize the indoor range error using the Dynamic Gaussian Model (DGM). In this work, initially a Gaussian approximate paradigm is built and the rapid LOS or NLOS flaw at an average time dynamically is taken as shift from the approximation. As per this drift, estimation adjustment is proposed which diminishes the error.

Time Reversal (TR) is another technique useful in achieving centimetre level accuracy in the presence of multipath in IPS. TR method can focus the vitality of the sent signal on to the planned area and this is otherwise called spatial centering impact. Wu et al. (2015) proposed TR based IPS (TRIPS) for single AP working in NLOS. It involves two aspects; the first is off-line where, the data index of Channel Impulse Response (CIR) is constructed. This is to outline physical topographical area into the legitimate area in the CIR area. The second stage is online stage where, the evaluated CIR of the Terminal Device (TD) is coordinate with the CIR archive to confine the TD.

For accurate positioning at reduced cost, ultrasonic IPS is useful. Lindo et al. (2015) discussed two novel multiband waveform synthesis methods for ultrasound-based IPS. One is, $M$-channel Trans multiplexer for Complimentary Set of Sequences (CSS) and the other one is Interlace of Binary Phase Shift Keying (IBPSK). By simultaneous transmission of the CSS, the first scheme eliminates the need for using macro sequences which are used in traditional ultrasonic local position systems. The IBPSK scheme jelly the relationship properties of the non - coherent successions, (for example, Generalized Pairwise Complementary codes) and to distinguish them in non-cognizant structure.
Table 2.3 Recent approaches in positioning

<table>
<thead>
<tr>
<th>Scheme</th>
<th>Positioning systems</th>
<th>Indoor/Outdoor</th>
<th>Accuracy</th>
<th>Remarks</th>
</tr>
</thead>
<tbody>
<tr>
<td>Integrated Active Filter</td>
<td>FMCW</td>
<td>Both</td>
<td>Outdoor-15 cm, Indoor-32.88 cm</td>
<td>It does not need synchronization of BSs.</td>
</tr>
<tr>
<td>Light sensor based</td>
<td>Similar to IR</td>
<td>Both</td>
<td>Accuracy varies with light intensity</td>
<td>Economical and useful for smaller area. Not suitable for virtual reality applications.</td>
</tr>
<tr>
<td>Standalone RFID</td>
<td>Passive RFID</td>
<td>Indoor</td>
<td>1 - 2 m</td>
<td>The Positioning Errors (PE) can be diminished when setting the tags nearer to the way and additionally closer to each other.</td>
</tr>
<tr>
<td>FSkNN</td>
<td>FSkNN (RSSI)</td>
<td>Indoor</td>
<td>Within 1.69 m in 50% of the time.</td>
<td>The average location error is as low as 1.70 meter. FSkNN is useful in many indoor IoT applications.</td>
</tr>
<tr>
<td>Peer to peer NLOS</td>
<td>TOA/AOA (RSS)</td>
<td>Both</td>
<td>Compared with existing peer to peer techniques, Improved rate of 83% for Indoor and 54% for urban environment.</td>
<td>Location error standard deviation 3/4 rms of less than 1.6 m and 22 m for 90% of time for the indoor and outdoor environment respectively</td>
</tr>
<tr>
<td>Enhanced Zigbee</td>
<td>RSSI</td>
<td>Indoor</td>
<td>Within 1.25 m for 98.67% of time.</td>
<td>Provides better positioning accuracy than any individual method and a multi-expert approach.</td>
</tr>
</tbody>
</table>

continued …
<table>
<thead>
<tr>
<th>Scheme</th>
<th>Positioning systems</th>
<th>Indoor/Outdoor</th>
<th>Accuracy</th>
<th>Remarks</th>
</tr>
</thead>
<tbody>
<tr>
<td>3D optical</td>
<td>Similar to IR</td>
<td>Indoor</td>
<td>Accuracy varies with light intensity</td>
<td>For 2D, PE is 3cm at a physical separation among two nearby reference mark of 5cm. In 3D space, with vertical layers at interiors of 10cm, approximately 10cm of 3D PE, was noticed.</td>
</tr>
<tr>
<td>Visible Light</td>
<td>TOA(RSSI)</td>
<td>Indoor</td>
<td>In the order of millimetres or centimetres</td>
<td>Position estimation precision contingent upon the room shape, transmitted signal frequency and power, and LED and photo receiver properties.</td>
</tr>
<tr>
<td>Visible Light and Accelerometer</td>
<td>Light Intensity based</td>
<td>Indoor</td>
<td>Few centimetres</td>
<td>Does not require information of receiver’s height and requirement of the transmitter and the receiver be aligned to the ceiling. The average position errors of less than 0.25m.</td>
</tr>
<tr>
<td>Calibrating IPS</td>
<td>Wi-Fi(RSS)</td>
<td>Indoor</td>
<td>For 45 samples accuracy varies from 1.4m to 1.8m</td>
<td>A predictive analysis is used in the proposed approach which can be used to facilitate the positioning system planning at pre-deployment stage.</td>
</tr>
<tr>
<td>PDRg</td>
<td>Wi-Fi(RSS)</td>
<td>Indoor</td>
<td>Positioning accuracy is enhanced compared to Blue tooth or Zigbee based technologies.</td>
<td>Over the time the aggregation of PE is the main issue.</td>
</tr>
</tbody>
</table>
### Scheme | Positioning systems | Indoor/Outdoor | Accuracy | Remarks
---|---|---|---|---
Magnetic position | Magnetic field based | Indoor | In centimetres (exhibits average error of approximately equal to 0.7 cm) | Excellent material penetration properties, more suitable for use in harsh NLOS conditions. The system exhibits a maximum position in error of 10 cm in an indoor environment over a 3 x 3 m² area.

Real time RFID | RSSI | Indoor | Better accuracy than classical RFID | Suitable for personal navigation application or mobile commerce application.

DGM | RSSI | Indoor | When estimation error is greater than 3 m, this method has 3% better accuracy than PF. | The estimation accuracy is greatly improved without imposing complexity and suitable for the dynamic indoor environment.

TR | RSSI | Indoor | 10 cm localization accuracy (within 0.9 m by 1 m area) | Indeed, even just with a solitary AP, for the small indoor area, this scheme produces better estimation.

IBPSK | Ultrasound | Indoor | Accuracy depends on correlation properties determined by the spreading sequences. | Compared to BPSK, in IBPSK, the transmission span is diminished to 37.44%. This decreases the energy intake of the emitters without debasing the accuracy.
2.5 Conclusions

This chapter surveys the recent advances in IPS and techniques. Different wireless positioning solutions and navigation techniques are discussed. Each of these systems/techniques has their own characteristics in terms of scalability, availability and measurable performance when applied in real time environments. Various performance measuring metrics and several trade-offs among the different systems are observed. It is clear that, the choice of algorithm/technique/system plays an important role on granularity and accuracy of location information.

Other than different techniques accessible for IPS, the present arrangements can’t adapt to the execution level prerequisite of various usages. By and large, the greater part of the applications necessities are improved precision, accessibility and coverage with minimal effort usage. A decent measure of research both from industry and the scholarly community are needed to accomplish these requests. A portion of things to come inclines in wireless IPS are as pursues:

1. New hybrid IPS offers for 4 G and tracking with available positioning frameworks (Zahid et al., 2013).

2. Need for building a new robust hybrid positioning system for integrating both indoor and outdoor localization.

3. Need for cooperative mobile localization. If group of nodes are detected then, developing application like formation of mobile ad hoc network on the located nodes could be another area to explore.

4. Channel State Information (CSI) is an upcoming system to supplant RSSI. It achieves higher robustness in fingerprinting methods than RSSI. As current smartphones only supports Wi-Fi enabled devices, specialized infrastructure is needed in existing systems (He and Chan, 2016; Wu et al., 2012; Yang et al., 2013).

5. The motion sensing (He and Chan, 2016), sound detection (Shangguan et al., 2014) techniques are available to enable the physically challenging people in accessing the IPS. More optimization in terms of usage, cost and accuracy in this regard is needed.