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NLOS Identification and Mitigation Indoor Localization: Theory, Methods, Technologies

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ABSTRACT

The recent years has seen a lot of research in indoor localization and location services. Wireless location finding is one of the key technologies for wireless sensor networks. The GPS technology used for outdoor localization, but when to deal with indoor localization GPS solution is inadequate. Indoor locations include buildings like supermarkets, big malls, parking, universities and locations under the same roof. The indoor environments are very challenging and, as a result, a large variety of technologies have been proposed to cope-up with them, but no legacy solution has found. Even the existing solutions are better suitable for LOS environment but these cannot work effectively for NLOS situations. Various applications, such as localization of persons and objects could benefit greatly from non-line-of-sight (NLOS) identification and mitigation techniques. This paper presents the survey for different methods, technologies for effective NLOS indoor localization. In this study, we propose two accurate approaches using only received signal strength (RSS) measurements from Wi-Fi signals to identify NLOS conditions and mitigate the effects.

Keywords: LOS (Line of Sight), NLOS (Non-Line of Sight), Wi-Fi, GPS, Smart Phone, IPS (Indoor Positioning System).

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I. INTRODUCTION

The last few decades have seen very explosive research on technologies for outdoor tracking with navigation and localization. Wireless location finding is one of the key technologies for wireless sensor networks. GPS is the technology used but it can be used for the outdoor location. When to deal with the indoor locations GPS does not work[2]. Indoor locations include buildings like supermarkets, big malls, parking, universities and locations under the same roof. In these areas the accuracy of the GPS location is greatly reduced. A scenario where people spend most of the time of the schedule in indoor environment. Hence it become a need of reliable, accurate real-time indoor tracking and localization system. . So to find out the accurate location for indoor environment we use the RSSI- based trilateral localization algorithm [1] [2] [7]. The localization schemes for wireless ad-hoc networks is classified as a ranged based and connectivity based localization, where ranged based attempts to perform position estimation by estimating the distance or direction, wherein connectivity based the location of an UN is inferred by its proximity to several RN.

Indoor real time locating systems (RTLS) have been gaining relevance due to the widespread advances of devices and technologies and the necessity for seamless solutions in location-based services. An important component of RTLS is indoor tracking where objects, vehicles or people (in the sequel referred to as mobile nodes) are tracked within a building or any enclosed structure. This paper presents a survey on indoor wireless tracking of mobile nodes from a signal processing perspective. It can be argued that the indoor tracking problem is more challenging than the one on indoor localization [8] [9]. The reason is simple from a set of measurements one has to estimate not one location but a series of correlated locations of a mobile node.

A current trend in addressing indoor tracking is to use standard, low-cost, and already deployed technologies. One driver of this activity is the enabling of smartphone-centered indoor positioning systems (IPSs). The technologies used in these systems are highly heterogeneous, encompassing Wi-Fi, UWB, radio-frequency identification (RFID), Bluetooth, near-field communication (NFC), 3GPP/LTE, signals of-opportunity, and inertial measurement units (IMUs). The localization schemes for wireless ad-hoc networks is classified as a ranged based and connectivity based localization, where ranged based attempts to perform position estimation by estimating the distance or direction, wherein connectivity based the location of an UN is inferred by its proximity to several RN. The existing IPS systems used the RSSI-based methods of localization like lateration technique such as trilateration, multi-lateration, [1] [2] [8] triangulation methods of localization using pathloss model for signal propagation to improve accuracy of localization. Various wireless system can be employed for indoor environment. Many of the systems makes use of existing infrastructure like Bluetooth, RFID, Wi-Fi, etc. By comparing previous localization accuracy must increase with decrease in performance time [1] [8].

II. TYPES OF MEASUREMENTS

This section presents the types of measurements used for the localization are classified as either geometric -related or self-positioning measurements information on node acceleration and orientation. These geometric measurements are categorized further as ranged-based and connectivity- based.

1. Geometric- related Measurements:

The optimum approach to manage the measurements (e.g., the received signal) is to use them directly as input y_m to the tracking estimator, but due to some limitations and implementation constraints this can be achieved through 2-steps approach. Firstly estimating geometric quantities from signal features and then feeding these values with tracking estimator (two-step estimation). These geometric based are of two types: ranged-based and connectivity based [2][8].

A. Ranged-Based Measurements:

Typically, these methods employ a two-phase process to provide position estimation for unknown nodes. Phase-I is ranging phase where distance /direction estimation is performed and in Phase-II result of Phase-I is used to compute co-ordinates(x, y) of unknown node. These methods are categorized as distance based and direction based [2][9].

1. Received Signal Strength (RSS)**:** Distance estimation based on received signal strength (RSS) measurements relies on the principle that the greater the distance between two nodes, the weaker their relative received signals. A widely used statistical model to characterize the RSS is given by,

$$\mathrm{Pr(d)} = \mathrm{P_0} - 10_\gamma \log_{10} \mathrm{d} + \mathrm{S} \qquad (1)$$

where, $Pr(d)$ (dBm) is the received signal power at a distance d from the emitter, P_0 is the received power (dBm) at a reference distance of 1 m (which depends on the radio and antenna characteristics as well as the signal wavelength), d (m) is the separation between nodes, and S (dB) represents the large-scale fading variations (i.e., shadowing). It is common to model S as a Gaussian random variable with zero mean and standard deviation σ. The main advantage of RSS-based approaches compared to other methods is the availability of RSS measurements in practically all wireless systems and the fact that the nodes do not have to be time synchronized. The most relevant drawback of RSS ranging is that in cluttered environments the propagation phenomena cause the attenuation of the signal to be poorly correlated with distance, especially in non-line-of- sight (NLOS) channel conditions, resulting in inaccurate distance estimates.

2. Time-of-Arrival (TOA)*:* Information related to the separation distance d between a pair of nodes can be obtained by using measurements of the signal propagation delay, or time-of-flight (TOF) [5].The ToA represented by a formula as,

$$\tau p = d/c \qquad (2)$$

Where, c is the speed of electromagnetic waves in air ($c \simeq 3 * 10_8$ m/s). This is usually accomplished using a two-way time-of-arrival (TWTOA) ranging protocol or time difference-of-arrival (TDOA) techniques. In TW-TOA ranging, a node A transmits a packet to node B which replies by transmitting an acknowledgment packet to A after a known or measured response delay τ_d [3]. Then the node-A estimates the signal round-trip time (RTT) $\tau_{RT} = 2\tau_p + \tau_d$, from which it can calculate the distance without the need of a common time reference [2] [5] [6].

3. Time-Difference-of-Arrival (TDOA): TDOA do not rely on absolute distance estimates between pairs of nodes. When the TDOA is used it may uses one of two methods, as multiple signals are broadcast from synchronized anchor nodes and the mobile node measures the TDOA, and another is that where a reference signal is broadcast by the mobile node and it is received by several anchor nodes. The anchor node shares their estimated time-of-arrival (TOA) and compute the TDOA [2] [9].

4. Angle-of- Arrival (AoA):

Angle-based techniques estimate the position of a mobile node by measuring the angle-of- arrival (AOA) of signals arriving at the measuring node through the adoption of antenna arrays. With perfect measurements, the positioning problem can be solved geometrically by finding the intersection of a number of straight lines representing the signals AOA (triangulation).

5. Phase-Difference-of-Arrival (PDOA): PDOA techniques were originally introduced for distance estimation in radar systems and have been recently rediscovered to improve the localization accuracy of RFID and WSNs systems. The basic version of PDOA consists in transmitting a couple of continues wave signals at frequencies f1 and f2, respectively, and measuring the phase difference at the receiver that results to be proportional to the distance and inversely to the difference f2 − f1.

6. Time-of-Flight (ToF): In this method using the time-of-flight and the known speed of the signal, the distance can be computed using speed-distance relationship. ToF can be used with RF, acoustic, infrared and ultrasound signals. The only drawback of this method is, it requires complex hardware for perfect synchronization when only RF signal is used. Wi-Fi ToF approach is geometrical, which calculates RTT instead of time offset.

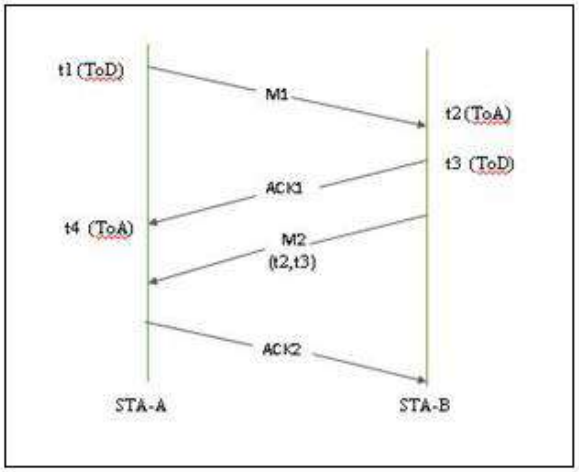

Figure1: ToF Protocol

$$ToF = \frac{(t4-t1)-(t3-t2)}{2} \quad (3)$$

Where, t1, t3 are ToD and t2, t4 are ToA signals respectively from station A and B.

7. Proximity: The binary connectivity is used to estimate the nodes' positions at time n. The location information is provided from the proximity of the mobile node to some of the anchor nodes in the system [2]. A key advantage of the proximity technique is that it does not require any dedicated hardware and time synchronization among the nodes.The all discussed method of geometric measurements are distance-based methods. Triangulation method is direction-based method of geometric measurement [2] [11].

8. Direction-based Method (Triangulation): This is geometric positioning measurement, work in two phase as, angle estimation and position calculation. In phase-I, angular bearings of the unknown node relative to least 3-reference nodes are estimated. From the angles obtained in the previous phase the position is estimated using triangulation. And in next phase (phase-II) the position of unknown node is estimated using trigonometry laws of sines and cosines.

$$Sine: \frac{A}{\sin a} = \frac{B}{\sin b} = \frac{C}{\sin c} \quad (4)$$

$$\text{Cosine:} \quad \begin{aligned} C^2 &= A^2 + B^2 + 2AB\cos(c) \\ B^2 &= A^2 + C^2 - 2AB\cos(b) \\ A^2 &= B^2 + C^2 - 2AB\cos(a) \end{aligned} \quad (5)$$

B. Connectivity-Based Measurement:
This is Range-free measurement of geometric measurement. In this unknown nodes find their location based on their proximity to the reference nodes. The unknown nodes estimate connectivity relationship to sufficient number of reference node instead of estimating distance or angles. The unknown node obtains the connectivity constraints to the reference nodes from the communication with these nodes. And finally estimates position.

2. Self-Measurement: Inertial Measurement Unit:

INS systems based on laws of motion. If the initial speed and all forces acting on the object is known, its movement can be estimated [] [2].Most handheld devices incorporate small and light IMUs based on microelectromechanical systems (MEMS) technology. Typically, an IMU is composed of three orthogonal gyroscopes and three orthogonal accelerometers. The INS systems makes use of inertial sensors such as accelerometer, gyroscope, and magnetometer which are built in with smart phones that can be used in position estimation. These triads of sensors measure angular velocity and a specific force, respectively, IMUs are very popular in navigation systems, especially when they are integrated with other technologies [1] [12] . The reason is the complementarity of errors between inertial sensors and the geometric-based approaches for position estimation. While an INS provides very accurate acceleration (and thus position) measurements, it produces an error that increases over time because of the sensor biases [2] [12].

III. LOS/NLOS IDENTIFICATION AND MITIGATION

NLOS Identification is a crucial parameter in this research because it enables the ability to only mitigate ranges that are strictly NLOS. This saves processing time and ultimately can lead to increased battery life if the processing is done on a mobile node. In actuality, a common problem in many localization techniques is NLOS error mitigation[3] [4]. NLOS error directly affects many localization accuracies in WSNs. This subsection introduces the research results to mitigate NLOS errors. NLOS errors between two sensors can arise when either

the line-of-sight between them is obstructed, perhaps by a building, or the line-of-sight measurements are contaminated by reflected and/or diffracted signals. As NLOS error mitigation in AOA based localization [2] [5] and distance based localization. Guvenc in [11] proposes NLOS identification using channel statistics such as CIR. Michl in [6] goes further and also classifies NLOS by severity. It is classified as being "hard" or "soft". Hybrid schemes are common solutions proposed in an attempt to achieve a more accurate position. Wen, Niki, Andrew [7] states that it is reasonable to combine multiple schemes to achieve an accurate position and proposes a geometrical hybrid ToA/AoA scheme. In hybrid schemes the filters are involved as position estimators named as Kalman filter and particle filter and their advanced types [4] [6] [7].

The Kalman filter is a commonly used predictive approach to NLOS mitigation. The Kalman filter uses additional measurement inputs that are acquired over time. But the disadvantage Kalman filter gives less accuracy than particle filter and computational time is higher. On other hand particle filter requires extra computational hardware but gives accurate position estimation and faster in execution. And PF also supports multi-modal object tracking. LOS is defined as both the transmitter and receiver having a clear path between them with no obstructions between them. NLOS is the opposite of LOS, where there is an obstruction between the transmitter and receiver and the signal must use non-direct paths to reach a node, thus not taking the shortest path. The below two scenarios are discussed:

A. Line-of-Sight Scenario:

The ToA technique under LOS conditions is shown in figure2, the t_{prop} is seen as being 1 nanosecond, thus given the speed of light, the distance is calculated from (6), which results in 0.3 meters [3][5]:

$$d = ct_{prop} \tag{6}$$

Where, c, is the speed of light through free space and $tprop$ is the propagation time of the radio signal.

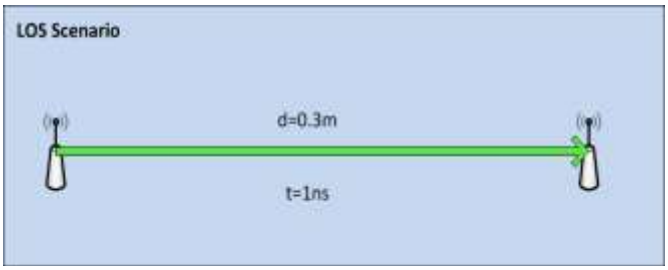

Figure3. LOS in ToA technique.

B. No Line-of-Sight Scenario:

The weakness of ToA is seen when NLOS occurs .In NLOS conditions, wireless signals that cannot pass through an object must reflect from walls or diffract from an object to reach a target node. Reflection and diffraction of a wireless signal will occur in LOS situations as well but the first signal to reach a receiver will be the direct, unobstructed path. Incoming reflected/diffracted signals entering a receiver are then discarded [4] [6].

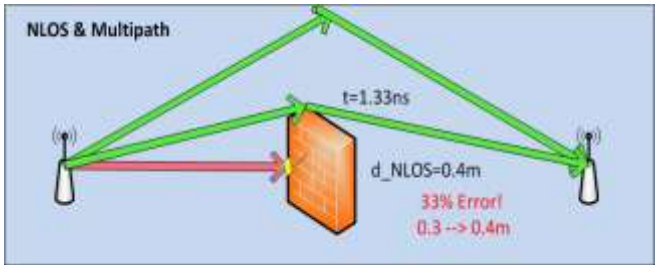

Figure 4. NLOS and Multipath

In NLOS conditions, the incoming received signal is a result of the reflected and/or diffracted signal. This causes t_{prop} be greater than it should be, which causes calculated distance to be greater. Theoretically in NLOS conditions, the time and distance calculated must always be greater than the time and distance in an LOS path. The size and position of an NLOS causing obstruction also affects the ToA range calculation. Hence the proposed system worked with the ToF ranging model involving the particle filter as position estimator [4] [5] [7].

IV. PROPOSED SYSTEM

The propose IPS system works as follows: first system uses the of RSS-based trilateration for initial localization of the unknown node and then using ToF range model distance between assistant and unknown node is calculated at the same time identifying and eliminating ToF ranging and NLOS errors using PF.

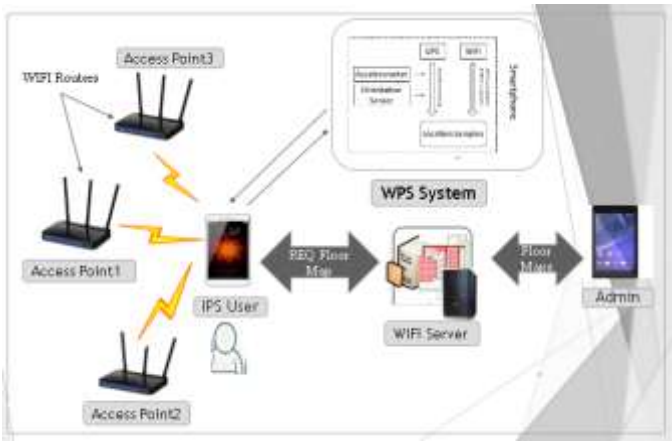

Figure5. Proposed IPS Architecture

1. Initial Localization:

The initial localization where the model-based approach of RSS based localization is used to get the initial RSS measurements of unknown nodes and surrounding nodes are acquired using traditional RSS based localization algorithm i.e. trilateration. The trilateration localization method works with two steps as first to distance estimation using path-loss model and localization [2] [7] [11]. Log-normal Path Loss Model:

$$Pr = PtGtGr \frac{\lambda 2}{(4\pi d)2} \quad (7)$$

Where, $\frac{\lambda 2}{(4\pi d)2}$ is FSPL, P_r is receiver's power, P_t transmitter's power, G_r and G_t gain of receiver and transmitter. In equation (2) where, X σ is random shadowing effect, that is varies depends on the measurement units of frequency (f) and distance (d).

$$PL(d)[db] = PL(d) + X\sigma = PL(d0) + 10\gamma \log\left(\frac{d}{d0}\right) + X\sigma \quad (8)$$

As shown in figure-6 the trilateration gives the position of mobile node as the intersection of three circles gives the possible position node. To achieve more accuracy no of access point s are increased.

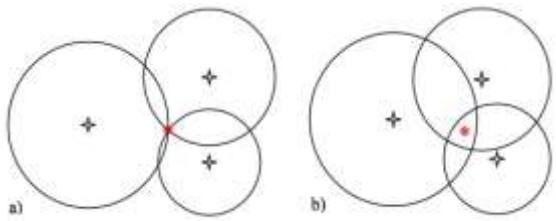

Figure.6: Trilateration Localization

2. ToF and NLOS Error Identification and Mitigation:

The proposed system works with complex indoor environment, and due to presence of human and environmental obstacles in complex environment the wireless channel may be blocked. The presence of NLOS will result into the signal reflection, refraction, multipath fading and signal penetration which will in turn caused the degradation in location accuracy and speed of localization [7] [8] [9]. To improve the localization accuracy of mobile node in NLOS environment, the strategy consists of two steps: NLOS identification and mitigation.

A. NLOS Identification:
For TOA measurement the standard deviation of the, measurement can be expressed:

$$\sigma k = \sqrt{\frac{1}{N}\sum_{x=1}^{N} [Dk(t) - A(Dk(t))]\,2} \quad (9)$$

Where $Dk\ (t)$ is distance between mobile node (unknown node) and kth access point (nearest) at time t and $A(Dk(t))$ is mean of measurement distance. Since the value of $A(Dk(t))$ is an unknown and using least square method the equation (6) becomes,

$$\sigma k = \sqrt{\frac{1}{N}\sum_{x=1}^{N} [Dk(t) - pk(t)]\,2} \quad (10)$$

According to the SD of measurement of error of TOA observation the current sight state can be estim6ated by:

$$S(t) = \begin{cases} 0, & \sigma k < \gamma\sigma 1 \\ 1, & \sigma k \geq \gamma\sigma 1 \end{cases} \quad (11)$$

Here the sight state S=0 corresponds to LOS propagation and S=1 corresponds to NLOS propagation.

B. NLOS Mitigation using Particle filter (with PDR):

The particle filter is used as location estimator. PF is sequential Monte Carlo method [5] [6] [7] [8]. The key idea is to use a series of random variables to represent posterior pdf (probability density function) of the system, and to get estimate value of state. The PF is used with the PDR and ToF ranging model to improve the accuracy and speed of localization by using some inbuilt IMU (Inertial sensors) like accelerometer, gyroscope and magnetometer.

The PDR works in 3 phase as follows:

1. State Transition Detection: Transition detection is performed based on the data collected from accelerometer. Two stages of particles are defined as stable and unstable. This stages are detected by the acceleration values.
2. Step Counting and Stride Estimation: It's performed to calculate the walking distance of the user. And the human stride is determined by dynamically checking the acceleration sequence.
3. Heading Detection: The mobile's magnetometer used to provide the heading orientation of the phone relative to the magnetic north to induce the user walking direction.

Particle Filter:

The PF takes input from PDR and NLOS identification module to estimate position in NLOS environment. In particle filtering, the conditional state density $p(X_t\,|Z_t)$ at time t is represented by a set of samples{ $S_t^{(n)}: n = 1,2,\ldots,N$ } (particles) with weights $\pi_t^{(n)}$ (sampling probability). The weights define the importance of a sample, that is, its observation frequency.

The PF estimates location in 3 phases:

1. Prediction Phase: To take each particle and add a random sample from the motion.

$$S_{t|t-1} = \{X_{t|t-1}^{-(i)}, W_{t-1}^{\sim(i)}\}_{i=1}^{n} \quad (12)$$

2. Update Phase: Weight that is equal to the probability of observing the sensor measurements from that particle's state.

$$w(\vec{x}_{0:t}) = w(\vec{x}_{0:t-1}) \cdot \frac{p(\vec{y}_t|\vec{x}_t) \cdot p(\vec{x}_t|\vec{x}_{t-1})}{q(\vec{x}_t|\vec{x}_{0:t-1}, \vec{y}_{1:t})} \quad (13)$$

3. Resample Phase: A new set of particles is chosen so that each particle survives in proportion to its weight.

$$S_t = \{x_t^{-(i)}, w_t^{\sim(i)}\}_{i=1}^{n} \quad (14)$$

V. CONCLUSION

The literature reviews the existing research results for WSNs localization techniques including measurement-based techniques and range-free localization techniques. Then, NLOS error mitigation is also analyzed. In this paper, we have proposed two NLOS identification and mitigation algorithms using only Wi-Fi RSS measurements using ToF ranging model and particle filter. NLOS conditions are identified classified and a target's NLOS position is successfully mitigated when only two LOS anchors are available by utilizing the physical geometry of the anchor distributions in a room. The model in this research assumed that the probability of one anchor experiencing NLOS out of three anchors is highest, thus a mitigation algorithm handling this most common case is proposed. The mitigation algorithm was able to mitigate a target's position, with increasing accuracy as the NLOS severity increased. The proposed system provides an advance technique for positioning and tracking a mobile device using collaborative method of RSS- based trilateration for initial localization with using inertial sensors like accelerometer, gyroscope and magnetometer and parallely working for NLOS error and ToF ranging error using adaptive particle filter. Hence providing a more accurate and faster localization system with robust system for NLOS and ToF ranging errors using particle filter and ToF Ranging method.

VI. FUTURE SCOPE

In future scope the proposed IPS system can be used with some hybrid approach to achieve the more accurate position estimation and can be used for multi-modal system. The proposed system can be used for multi-object tracking in complex indoor and NLOS environment using PF and modified-PF to achieve high accuracy and multi-object tracking.

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