Indian Journal of Engineering & Materials Sciences
Vol. 31, February 2024, pp. 7-24
DOI: 10.56042/ijems.v31i1.5183

Review Article

Conventional system to deep learning based indoor positioning system

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Received: 27 August 2023; Accepted: 2 February 2024

This review article presents the key fundamentals of indoor positioning system (IPS) and its progressing footprints. The need of IPS and work done with methodology adopted to implement IPS for various applications have been discussed. The evolution from conventional to deep learning (DL) has been presented, addressing various challenges existing in conventional IPS like poor localization, improper accuracy, non-line-of-sight problems, instability of signal due to fading, requirements of large infrastructure, data-set and labour, high cost, and their existing solutions have been disclosed. Further in order to compute the indoor positioning with acute precision various advanced positioning technologies including sensor fusion, artificial Intelligence (AI), and hybrid technologies have been explored. The issues and challenges existing in current IPS technology have been presented and future insights to work in this direction have also been provided.

Keywords: Artificial intelligence (AI), Deep learning (DL), Global positioning system (GPS), Indoor positioning (IP), Reliability, Sensor fusion (SF)

1 Introduction

In this digital era, by making use of the global positioning system (GPS) mapping of every inch of the world persists, and to navigate different locations Google maps, HERE We Go, Back Country Navigator, Map Factor, Maps. Me, MapQuest, Osm And, Sygic GPS, Polaris GPS Navigation, and Scout GPS Navigation[1], are prevalent. GPS is used to navigate in the outside environment. GPS is dependent on satellites. Received signal power of GPS signal obtained from satellites has low signal power at the receiver end because longer distance is travelled by it. Moreover, in the indoor environments, GPS signal is blocked and deteriorated by various parameters mainly by the walls and cannot be received properly resulting in degradation of signal strength which on counterpart increases the inaccuracy in the indoor environment[2]. So, there is an utmost requirement of an indoor positioning system (IPS) to accurately navigate, or position objects in the indoor environment of hospitals, railway stations, airports, shopping malls, offices, museums, and many more. IPS provides a solution to visually impaired people to accurately navigate in the real world complex indoor environment[3]. In unmanned aerial vehicles (UAVs), IPS helps in locating the target in the indoor environment, monitoring disasters in tunnels, and performing inspection tasks[4]. With the pace of increasing developments and automation in industries, the demand of IPS is on the rise. Autonomous robotic system uses IPS to inspect the civil infrastructure for data collection and processing[5]. In factories, by using IPS, accidents can be avoided; time consumed in various processes can be saved because of easy monitoring due to localization of various tools and machines[6]. IPS along with electroencephalogram (EEG) using eye tracking devices can be used in marketing research (Neuromarketing) by analyzing emotions of the customers about the various products at different locations[7].In supermarkets and shops, shopkeeper is guided by the IPS to find desired information about the stock along with existing offers as the customers pass near a product[8]. In hospitals, IPS provides assistance to the doctors to locate patients, within the specified range, in emergency condition, and can be provided the required treatment as soon as possible[9]. Despite the availability of various solutions like wireless local area network (WLAN)[10], wireless fidelity (Wi-Fi) technology[11], magnetic positioning[12], radio frequency identification[13], Bluetooth low energy beacons[14], visible light communication technology[15], etc., the essentiality of accurate, reliable, and the simple solution is desirable as these solutions result in higher computational complexity, improper accuracy, and

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poor reliability. The existence of security related issues and insufficient power processing in many positioning devices, compels to increase the database and other additional hardware for improving performance parameters, but overhead increases in terms of cost. Indoor positioning by inertial measuring unit (IMU) is based on inertial sensor data and thus it is not affected by external interference, rather than distance measurement in wireless signal transmission[16]. IMU is an electronic device that is composed of a gyroscope for measuring orientation, accelerometer for measuring linear acceleration and magnetometer for measuring the magnetic field[17]. Combination of measured data provides positioning of the object or a person. Further, there is a need to reduce sensor noise in the data obtained from sensors' measurements for accurately estimating positions or depth measurements for multi-storied building applications. To fulfil this requirement sensor fusion of IMU along with barometer is done using Kalman filter for noise reduction as shown in Fig. 1[18–22]. To reduce errors and to improve accuracy as well as prediction ability in the presence of external conditions, machine learning (ML) algorithms can provide efficient results with the reduction of root mean square error in the measurements.

Recently, artificial intelligence (AI) and ML algorithms are providing fascinating results because of their ability to make the valuable decisions according to data available and adaptively deal with the environment[21,23].

To resolve non-line-of-sight (NLOS) problems, AI-based various techniques either based on supervised or unsupervised ML techniques[24–26], and deep learning (DL) techniques [27] have been applied.

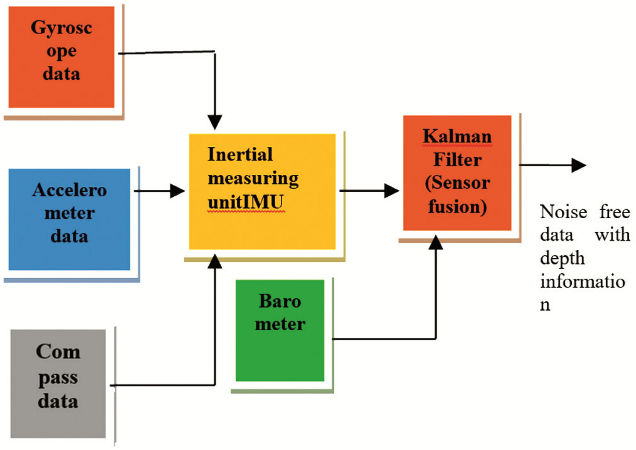

Fig. 1 — Sensor fusion of inertial measuring unit (IMU) and barometer.

The space requirement for storage and complexity in fingerprint data can be reduced by AI-techniques. Unknown environments can also be explored in robot navigation using DL techniques[28]. For multi-dimensional data collection from various sensor fusion methods and advanced ML techniques either supervised or unsupervised are quite essential[29–31]. Unsupervised ML techniques are more successful in the real time navigation environment.

This article describes the need of IPS in this modern era. Various conventional IPS methods exist but to get accurate location data is the main challenge. For improving accuracy, reliability, and noise removal, various sensor fusion and filtering algorithms have been described and to improve adaptation according to the changing environment model is trained using ML. To make IPS more robust and autonomous DL techniques have been described. To acquire better dimensionality, along with robustness, better accuracy and reliability in the IPSs, hybrid technologies have been discussed.

2 Materials & Methods

2.1 Work done and methodology adopted for various applications of indoor positioning

A lot of research work has been carried in indoor positioning. Some of the applications along with methodology are listed below.

2.1.1 Positioning in multi-floor building

Floor localization for 3 multistoried buildings with varying altitudes has been done using fusion of received signal strength (RSS) and barometer altimeter (BA) via kalman filter (KF). By using electronic hand held device, which is composed of barometer BMP280 (used for measuring barometric pressure), and radio Broadcom BCM43362 for determining RSS from Wi-Fi access points (APs) inside 3 multistoried buildings. Laser range finder has also been used to measure correct floor heights. The accuracy of 97.0%has been achieved for multi-floor localization[20]. To analyze the energy usage inside the building, it is necessary to understand how the individuals are utilizing the spaces of the building. In order to determine occupancy inside the building, smart phone kept in pocket based multi-floor indoor positioning (IP) system has been used. This system uses smart phone and its in-built integrated sensors: accelerometer, gyroscope, Bluetooth and Wi-Fi. Its positioning algorithm determines the direction for initialization using gyroscope and accelerometer data by using Mahony filter. The system uses the combination of gaussian Finger printing and bluetooth low energy (BLE) with the help of particle filter. As a result good performance in terms of accuracy for detecting occupancy information has been achieved[18]. For a multi-floor building, 3D localization has been done in which RSS has been enhanced by integrating it with sensor fusion of barometer, magnetometer, and inertial sensors' data *via* extended kalman filter (EKF). This resulted improvement in accuracy from 83.80% to 97%[32].

2.1.2 Positioning using micro-aerial vehicles and UAVs

Robotic control and visual localization has been done in micro-aerial vehicles (MAV) with the help of Indoor localization system using multi-sensor fusion on the basis of Ar Uco marker. The combination of markers, optical flow, ultrasonic, inertial measuring unit (IMU) has been used in multi-sensor fusion approach on the basis of federated Kalman Filter to minimize the impact of low quality images and strong illumination. Along with Grubbs criterion ArUco mapping algorithm has been used for building the online map along with its correction. The distortion in map has been corrected using K-means clustering algorithm. This system with 4×4 marker Array results in centimeter level mapping and positioning accuracy in MAV localization[33].The enhancement in dead reckoning solutions for indoor positioning using Quadrotor unmanned aerial vehicle (UAV) equipped with a Honeywell HMC5983 magnetometer, Inven Sense MPU 6000 MEMS-based IMU, TEMS5611 barometer, Marvelinind US beacon and a Sensirion SFM3000 mass flow sensor is achieved. Data collected from these sensors have been fused using EKF to determine position of UAV with improved attitude heading and reference system (AHRS) and Inertial Navigation System (INS). Maximum location accuracy of 95% has been achieved for distance of 4.3 m for 60 seconds[34].

2.1.3 Navigation using augmented reality

Combination of Augmented Reality (AR) and Global Positioning System (GPS) has been used to build an indoor positioning application. The data retrieved using GPS is in the form of latitude, longitude, and altitude. This data is stored in the cloud. Any user can use this data for determining location. User can select AR view mode which uses application's camera to view and process details of the location. *SQ Lite Open Helper* has been used for database management as it helps in creating, initializing and storing extracted location details in the database. Wikitude API helps in providing AI based location exposure. The application runs successfully under various conditions like varying lightning, geographical terrains, battery percentage, data pack and Wi-Fi [35].

2.1.4 Inspection of civil infrastructure

Inspection of civil infrastructure is very costly as it requires trained workers on various technologies and moreover manual inspection is prone to errors. Civil infrastructure inspection has been done by using autonomous and multifunctional robot which can be used in outdoor as well as in indoor environment. Inspection in outdoor is achieved using sensor fusion of IMU and GPS via EKF. To achieve indoor positioning for inspection, inertial information and stereo camera has been utilized in visual-inertial odometry mode. Non-destructive evaluation (NDE) is the data processing algorithm used to process data collected using various sensors: ground-penetrating radar (GPR), NDE, electrical resistivity (ER). convolutional neural network (CNN) is applied to detect cracks in civil infrastructure. The implemented system resulted in reduction of time for inspection[36].

2.1.5 Mobile robot localization

This is implemented using sensor fusion of IMU and laser scanner *via* recurrent neural network (RCNN). using robot operating system (ROS) named as Gazebo simulator, data is collected. This data is used to train RCNN model. The training of RCNN network is made at different sampling frequencies. The implementation of network is done in Pytorch frame work which has been trained using NVIDIA GTX1080 GPU. The network has been trained using ADAM optimizer for 50 epochs and 0.001 learning rate. As a result, it has been observed that architecture has the capability of self-localization even in challenging environments[37].

2.1.6 Outlier detection and removal

Due to unstable RSS of Wi-Fi Technology, outliers exist in the signal. The performance of the indoor positioning is degraded from the outliers. To resolve this issue for a pedestrian using smart phone, outlier detection and removal strategies have been used. This has been implemented using unsupervised hierarchical clustering algorithm of machine learning. Positioning for a static pedestrian is done using Wi-Fi and pedestrian dead reckoning (PDR). Positioning for walking pedestrian is carried out using hybrid approach by an inertial-navigation-system-based (INS-based) attitude heading reference system (AHRS) *via* extended kalman filter (EKF) to fuse pitch, roll, and magnetic inclination/declination on azimuth to determine azimuth of PDR. Location is determined using fusion of PDR and Wi-Fi using an unscented kalman filter (UKF) for both static as well as dynamic pedestrian using mobile's hand held positions. This hybrid scheme resulted in root mean square error (RMSE) of 1.43 m[38].

2.1.7 Food delivery

To reduce the labour cost, in restaurants food delivery robotic system is deployed using sensor fusion of compass, accelerometer and gyroscope data along with ultra wide band (UWB) using EKF. This results in 15 cm positioning error which is acceptable for restaurants[39].

Table 1 depicts the various applications of indoor positioning with their sensors, technology, and tools required.

3 Results & Discussion

3.1 Conventional indoor positioning systems

Indoor positioning is more complex than outdoor positioning due to indoor obstacles like walls and objects. Indoor positioning is computed in two phase i.e. a) ranging technique in which distance measurement step is accomplished between anchor nodes (with known location) and the target and b) estimation of the target position is accomplished from the observed distance[40]. The detailed discussion of different ranging and localization techniques is discussed in Section 3.1.1 and Section 3.1.2. In Section 3.1.3 other conventional indoor positioning techniques are being discussed.

3.1.1 Techniques for ranging

Ranging technique is based on distance measurement between the target and the anchor nodes. It can be based on time, time difference, angle, signal strength, channel-state-information as explained below:

- **Time of arrival (ToA):** For calculation of range, signal propagation time between base-station and target is used.

It is based on the principle of measurement of arrival time between the base-station nodes and the target node[41]. Figure 2 represents ToA with T as the target location, whereas T1, T2, and T3 are the time taken by 3 base-station nodes to reach the target T [42]. Using ToA, distance $\mathrm{D_m}$ of m^{th} base station from the target is calculated as follows:

$$D_m = c * t_m = \sqrt[2]{(x_m - x)^2 + (y_m - y)^2} \qquad \dots (1)$$

where, c is the speed of light in vacuum (3.0×10^8) m/s, $\mathrm{t_m}$ is the one way signal's time period of m^{th} base station while propagating in multipath, ($\mathrm{x_m}$, $\mathrm{y_m}$) is the location of m^{th} base station and (x, y) is the target's location represented in Eq. (1) [43].

- **Received Signal Strength Indicator (RSSI):** Received Signal Strength indicator (RSSI) is the relative signal strength or the quality of signal received by the receiving device or the receiver. Distance calculation is done from received signal strength. In the indoor environments, RSSI technique results in inaccurate distance measurements and fluctuations as it suffers from refraction, shadowing, fading and reflections. To cope up with these challenges ML and filtration techniques are being used. Figure 3 shows RSSI Positioning where, N1, N2, and N3 represent the nodes and T represents the target location[44]. RSSI can be modeled by the Rayleigh's or Racian's Eq. (2)[45] as follows:

$$\mathrm{P_{R1}} = \frac{\mathrm{G_{t1}.G_{r1}}}{4\pi}.\mathrm{P_{T1}}.\frac{\mathrm{h^2.\tau}}{\mathrm{D^{n1}}} \qquad \dots (2)$$

where, P_{R1} is the received signal power, P_{T1} is the transmitted signal power, the distance between the transmitter and receiver is represented by D, path loss exponent is represented by $n1$, h, and τ are the Rayleigh or Racian parameters, receiver gain in G_{r1}, and the transmitter gain is G_{t1}. Eq (3) represents the RSSI positioning technique used to estimate distance using Log Normal Shadowing model [45] as follows:

$$\mathrm{RSSI(D)} = -10\mathrm{n_p}\log_{10}(\mathrm{D}) - \mathrm{C_e} \qquad \dots (3)$$

where, $\mathrm{n_p}$ represents path loss exponent ranging from 0 to 5, and $\mathrm{C_e}$ is the environment constant.

- **Time Difference of Arrival (TDoA):** In TDoA technique, the time difference between the signal propagation between the anchor nodes and the target node is used for determining target nodes's position.

There is a requirement of atleast 3 anchor nodes for the calculation of the target location using hyperboloids' intersection. It suffers from synchronisation errors due to NLOS propagation and improper synchronisation of transmitters. To resolve this problem in TDoA and ToA many solutions for accuracy improvement are proposed[46–49].

Table 1 — Indoor Positioning for Various Applications

Reference No.	Application	Technology	
		Sensor or other technology	Tools
21	Accurate positioning in indoor navigation	Accelerometer, gyroscope and magnetometer measurements	MATLAB and NGIMU API
23	An Intelligent Actuator of an Indoor Logistics System	LIDAR, an RGB camera and an indoor inertial navigation, the actuator, odometer	Google's Ceres solver library, industrial personal computer (IPC) based on robot operating system (ROS)
93	3D-Positioning	IMU/magnetometer sensor, MEMS	MATLAB, a DC powered electric motor, Adis 16480 IMU, iPhone 3 GS camera mounted at the object's back site
94	3D-Positioning	INS, MEMS sensors, PDR	Trusted Positioning Navigator (T-PN)
95	3D-Positioning	Accelerometer, gyroscope, and magnetometer	Wi-Fi APs use Intel 8260 wireless cards and Ubuntu 16.04 LTS as hardware and software platforms, and Google Pixel 3 is used as MT which supports Android 9-based Wi-Fi FTM and can get real-time RTT and RSSI data from the surrounding Wi-Fi APs
32	Multi-floor 3 D-Localisation	Wireless received signal strength (RSS) and the data from inertial sensors, magnetometers, and a barometer	The test data was collected by using a Samsung S4 Android smartphone, equipped with gyroscope, accelerometer, and magnetometer triads, a barometer, a WiFi receiver, and a GPS receiver
96	3D-Mapping	Kinect RGB-D sensor, X sens MTi IMU, Hokuyo URG-04LX-UG01 LRF, and a notebook computer	-RGB-D SLAM, IMU/laser SLAM, and sensor fusion SLAM -GPU-SURF in OpenCV for feature detection
84	Museum Navigation and blind indoor navigation	Proximity sensors, Bluetooth low energy (BLE) beacons	T1RCI-00593 MANTO framework
97	Height Measurement	MEMS, GNSS/Inertial Navigation System (INS) device, barometer	Inertial Explorer software
98	Separated Sonar Localization System	LIDAR, Sonar sensor	virtual robot experimentation platform (V-REP) environment
99	Foot-Mounted Inertial-based Indoor Navigation Systems	Accelerometer, gyroscope and magnetometer measurements with two absolute fields, the Earth magnetic field and the gravity field, whose directions and intensities are known, help estimating the orientation	ZUPT
100	Navigation of unmanned ground vehicle	LIDAR (VLP-16) and camera sensors (LI-OV5640)	- ORB-SLAM2 -The network is implemented using the PyTorch framework and trained using an NVIDIA Titan X Pascal GPU based workstation
101	Daily life activity recognition	Microphone, Wi-Fi scan module, heading orientation of the device, light proximity, step detector, accelerometer, gyroscope, magnetometer	The J48 pruned tree is utilized for final ADL recognition. To manage complex data pipelines of batch jobs, data pipeline management frameworks are recommended such as Luigi Airflow, Pinball
88	Human localisation	Environmental sensors (PIR) and wearable sensor (IMU)	MATLAB 2017
102	Surgical instrumentation tracking	Epipolar geometry for the binocular system using two cameras, trifocal tensor for the three-camera system, and bundle adjustment in the N-camera system	V-REP PRO EDU robotic simulator, MATLAB, and CVX, a package for specifying and solving convex programs

Figure 4 represents TDoA positioning with T as Target node, A1, A2, and A3 as anchor nodes[50].

For the determination of distance using TDoA based on Linear solution algorithm, following equation is used:

$$\Delta\gamma = \begin{cases} G^{-1}\Delta\sigma & for \quad n \le 4 \\ (G^TG)^{-1}G^T\,\Delta\sigma & for \quad n > 4 \end{cases} \qquad \dots (4)$$

In Eq. (4) [51] offset of user's position from the linearization point is represented by the linear function, $\Delta\sigma$. Number of base stations is represented by n, user's coordinates are (x_{us}, y_{us}, z_{us}), nominal point's coordinates are $(\hat{x}_{us}, \hat{y}_{us}, \hat{z}_{us})$, base station coordinates are (x_{bi}, y_{bi}, z_{bi}), σ is the distance between user and base station, $\hat{\sigma}$ is the distance between the user and the nominal point. $\Delta\sigma = \begin{bmatrix} \Delta\sigma_1 \\ \Delta\sigma_2 \\ \Delta\sigma_3 \\ \Delta\sigma_4 \end{bmatrix}$,

$$G = \begin{bmatrix} a_{xb1} & a_{yb1} & a_{zb1} & 1 \\ a_{xb2} & a_{yb2} & a_{zb2} & 1 \\ a_{xb3} & a_{yb3} & a_{zb3} & 1 \\ a_{xb4} & a_{yb4} & a_{zb4} & 1 \end{bmatrix}$$

where, $a_{xbi} = \frac{x_{bi}-\hat{x}_{us}}{\hat{r}_{bi}}$, $\Delta\sigma = \hat{\sigma} - \sigma$, $\Delta x_{us} = \hat{x}_{us} - x_{us}$, $\Delta y_{us} = \hat{y}_{us} - y_{us}$, $\Delta z_{us} = \hat{z}_{us} - z_{us}$, $\hat{r}_{bi} = \sqrt{(x_{bi}-\hat{x}_{us})^2 + (y_{bi}-\hat{y}_{us})^2 + (z_{bi}-\hat{z}_{us})^2}$, $a_{ybi} = \frac{y_{bi}-\hat{y}_{us}}{\hat{r}_{bi}}$, $a_{zbi} = \frac{z_{bi}-\hat{z}_{us}}{\hat{r}_{bi}}$, and $\Delta\gamma = \begin{bmatrix} \Delta x_{us} \\ \Delta y_{us} \\ \Delta z_{us} \\ -c\Delta t_{us} \end{bmatrix}$, c is constant, and Δt_{us} is the time required.

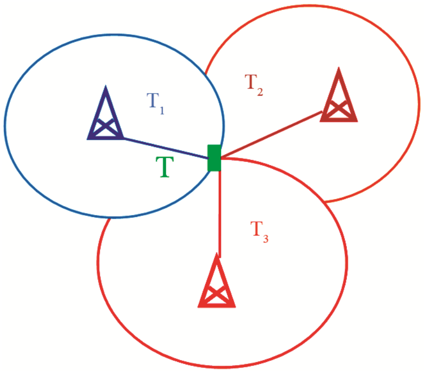

Fig. 2 — Time of arrival (ToA).

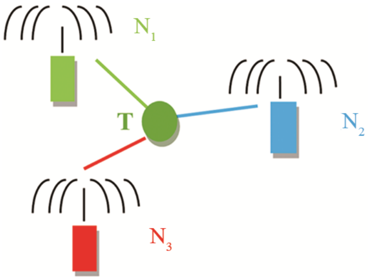

Fig. 3 — Received signal strength indicator (RSSI) Positioning.

- **Channel-State-Information (CSI):** Channel properties of communication links are represented by Channel-State-Information (CSI). It represents the way of propagation of signal from the transmitter to the receiver and includes combined effects like fading, scattering, and the decay of power with distance. Accurate estimation of received signal over the complete bandwidth signal can be achieved with enhanced ranging technique, i.e. CSI.

High-dimensional information is provided by CSI as in this information of time of flight (ToF) and angle of arrival (AoA) is derived from multiple orthogonal frequency division multiplexing (OFDM) sub-carriers. Multiple antennas are required in CSI and the estimation of frequency response of every antenna is required[52]. The phase and magnitude of the channel response can be provided by CSI for both range free and range based localisation schemes. Figure 5 represents CSI in which $T_{X_{u,v}}$ is the transmitted signal in channel (C) from the u^{th} transmitting antenna on v^{th} subcarrier. $R_{X_{u,v}}$ is the received signal represented in Eq. (5)[53] as follows:

$$R_{X_{u,v}} = T_{X_{u,v}}\mathrm{C}_{\mathrm{u,v}} + N_O \qquad \dots (5)$$

where, $\mathrm{C}_{\mathrm{u,v}}$ represents the changes caused by the channel in the received signal, and N_O is the noise.

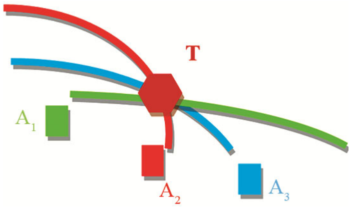

Fig. 4 — Time Difference of Arrival (TDoA) Positioning.

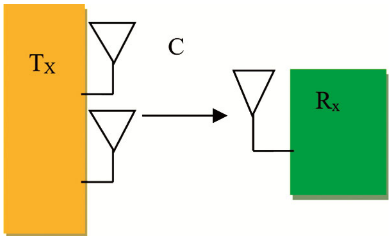

Fig. 5 — Channel-State-Information (CSI).

- **Angle of Arrival (AoA):** Angle made by the signal with the antenna is used in AoA technique. At least 2 anchor nodes are needed, as both distance as well as angle measurement are used. Figure 6 shows AoA technique where, T(x, y) is the target and B1(x1, y1), and B2 (x2, y2) are the positions of 2 anchor nodes angles θ_1 and θ_2. Position estimation of the target can be done using Eqs. (6) and (7) [54], respectively:

$$y = \frac{y_2 tan\theta_2 - x_2}{tan\theta_2 - tan\theta_1} \qquad \dots (6)$$

$$x = ytan\theta_1 \qquad \dots (7)$$

3.1.2 Methods of localization

The distance estimated by the ranging techniques is used for the location estimation. For indoor positioning following localisation methods are generally used:

- **Triangulation:** The estimation of location of the target is done by considering several reference points using angles i.e. angulation which can be measured by AoA algorithm. In the similar way, lateration is used for positioning using triangulation in which measurement of target's distance is estimated from several reference points. RSSI, ToA, TDoA, signal attenuation are some of the algorithms for the calculation of the lateration. Increase in the number of reference nodes can lead to the enhancement of localization performance. Figure 7 represents localization using triangulation in which B1, B2, and B3 are the 3 reference points or base stations and T is the target location [55]. The vertical position of the target point T at angle θ can be estimated[56]by using Eq. (8):

$$z_v = z_{vi} + (d_{vi} - d_v)cos\theta \qquad \dots (8)$$

where, z_{vi} is the vertical position of the base-station, d_{vi} is the distance of the vertical position of the i^{th} base-station z_{vi} from the reference point, and d_v is the distance of the vertical position of the target from the reference point.

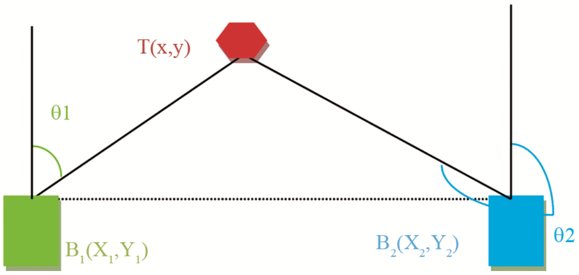

Fig. 6 — Angle of arrival (AoA) technique.

- **Trilateration and Multilateration:** In multiration, the position estimation of the unknown node is done using 3 or more nodes. The determination of position of an unknown node with 3 nodes is called trilateration. The intersection of 3 circles are sufficient for the estimation of 2-Dimensional position of the target node. But due to the persistence of NLOS, the intersection of 3 circles at one point is difficult. This leads to an increase in positioning errors which need to be mitigated. Least-square, and hybrid techniques are some of the methods presented for the mitigation of errors which results in inaccuracy[57,58].

Figure 8 represents multilateration (trilateration) where, (g, h) is the target location, whereas (g_1, h_1), (g_2, h_2), and (g_3, h_3) are the reference nodes in 2-Dimensional space. The position of the target (g, h) is estimated by using the equations (9), (10), (11)[43].

$$d_1{}^2 = (g - g_1)^2 + (h - h_1)^2 \qquad \dots (9)$$

$$d_2{}^2 = (g - g_2)^2 + (h - h_2)^2 \qquad \dots (10)$$

$$d_3{}^2 = (g - g_3)^2 + (h - h_3)^2 \qquad \dots (11)$$

where, d_1, d_2, and d_3 represents known distances estimated using ranging techniques.

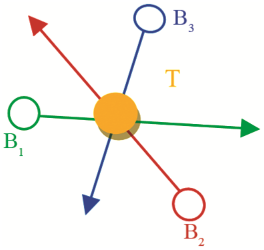

Fig. 7 — Localization using triangulation.

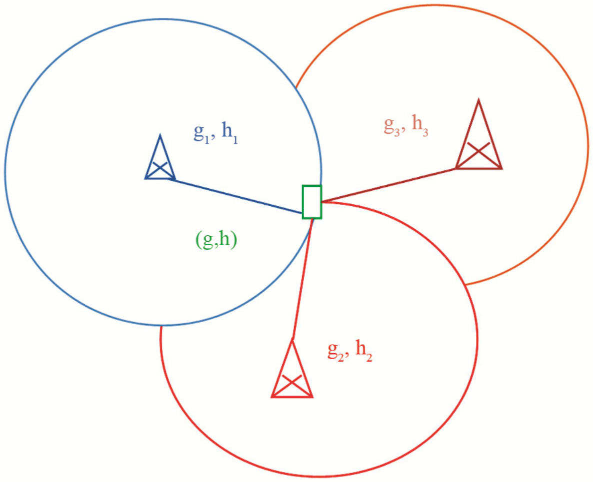

Fig. 8 — Localization using multilateration (trilateration).

- **Centroid:** The estimation of target location is done by using geometric relation by measuring angle or distance.

Figure 9 depicts localization using centroid technique in which A1, A2, and A3 are the anchor nodes used for the determination of the target T[55].

In this position of target determination is done only when there is establishment of stable communication between the target and every anchor node. To estimate the location of the target T with coordinates (a, b) using m number of anchor nodes, calculation of arithmetic mean of anchor nodes is required which isdescribed in Eqs. (12) and (13)[59], respectively.

$$a = \sum_{j=1}^{m} a_j\, k_j \qquad \ldots (12)$$

$$b = \sum_{j=1}^{m} b_j\, k_j \qquad \ldots (13)$$

where, (a_j, b_j) is the known location of j^{th} anchor node, k_j represents the weight of j^{th} anchor node.

- **Fingerprinting:** Fingerprinting is accomplished in two main steps:

a. Training of data in offline phase: At various access points, fingerprint databases using CSI or RSSI techniques are constructed and trained for various specified indoor positions.

b. Testing by positioning using trained dataset in online phase: In this, probabilistic approach is adopted for determination of the target location in which the measured data at various access points is compared with the database's stored data at various specified access points.

A great effort is needed for the construction of a database of a larger area. There is a necessity of the recreation of the whole database if there is change in even one of the nodes. More offline data is needed for providing better accuracy. So, to resolve these problems, AI is required. Figure 10 shows indoor positioning using fingerprinting, where, AP1, AP2, and AP3 are the access points and T is the target location[60]. The procedure adopted for localisation using fingerprinting is offline / online / Matching Algorithm Phase are represented in Eqs. (14)-(16) [61], respectively.

Offline Phase:

$$c_{pj} = \left[(N_j^1; L_j^1), (N_j^2; L_j^2), (N_j^3; L_j^3)\right]\ j = 1, 2, 3 \ldots, M \qquad \ldots (14)$$

where, c_{pj} is the position class with coordinates of j^{th} access point (AP), N is the major number, M is the total number of access points, $(N_j; L_j)$ is the beacon object, L is the RSSI related to that beacon.

Online Phase:

$$c_{pm} = [(N_m^1; L_m^1), (N_m^2; L_m^2), (N_m^3; L_m^3)] \qquad \ldots (15)$$

where, c_{pm} is the measurement vector, and $m = 1, 2, 3 \ldots, M$

Matching algorithm:

$$d_j = \min d(c_{pj}, c_{pm})\ \ j = 1, 2, 3 \ldots, M \qquad \ldots (16)$$

where, d_j is the position class with shortest distance between data points of access points and the new data points in the database. Thicker is the APs' distribution, higher is the accuracy. Relative position of user and access point is related by R-parameter. If R=1, then the user is close to AP, otherwise R=0.

- **Distance Vector (DV) Hop:** In distance vector (DV) Hop method, distance vector is estimated in a multi-hop environment. The average hop size hs_l is calculated, then the distance between node and the anchor node (n hops away from the node) is measured as $n * hs_l$. Figure 11 represents localization using DV Hop, where, A_N1, A_N2, A_N3 are the anchor nodes[62]. Each anchor node is composed of node identification number i_l, node location (x_l, y_l), and hop value i.e. h and sends (i_l, x_l, y_l, h) to the neighbouring node.

The average distance of each anchor node is computed using Eq. (17)[63] as:

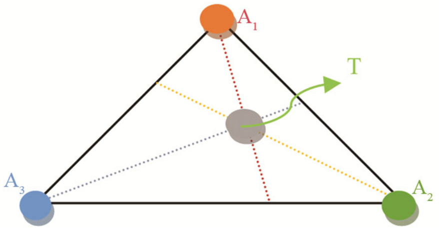

Fig. 9 — Localization using centroid.

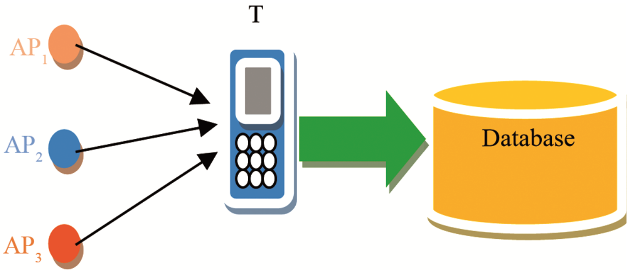

Fig. 10 — Localization using fingerprinting.

$$hs_l = \frac{\sum_{l\neq m}\sqrt{(x_l-x_m)^2+(y_l-y_m)^2}}{\sum_{l\neq m} h_l} \qquad \ldots (17)$$

where, (x_l, y_l) is the location of l^{th} beacon node, and (x_m, y_m) is the location of m^{th} beacon node, h_l is the minimum hop-value.

3.1.2 Indoor positioning technologies

In indoor positioning, there is a communication between networks of devices and internal sensors for smart-phones or tablets for calculation of indoor position based on mathematical algorithmic technologies like Wi-Fi, WLAN, Visible Light Communication, Bluetooth Low Energy (BLE) beacons, RFID and Magnetic Positioning.

- **Wi-Fi Technologies:** In this user's position determination is based on information of the received signal strength[64].
- **WLAN:** It comprises wireless access points that allow location tracking and monitoring in complex environments. Figure 12 represents indoor positioning using Wi-Fi and WLAN where, AP1, AP2, and AP3 are the access points[64].
- **Visible light communication:** In this the information is transmitted by visible light signal in the light space to track the device's position.

Figure 13 shows indoor positioning using visible light communication in which Rx is the receiver, where, Tx1, Tx2, and Tx3are the transmitting light sources[65].

- **Bluetooth low energy (BLE) beacons:** It is a type of short distance communication in which a beacon signal is detected by the mobile device and the distance is calculated from the beacon. In this way, location is estimated. Figure 14 shows indoor positioning using BLE beacon[66].
- **Radio frequency Identification (RFID):** It consists of a reader and a tag. Radio frequency electromagnetic field is used by a reader for reading data from the tag.

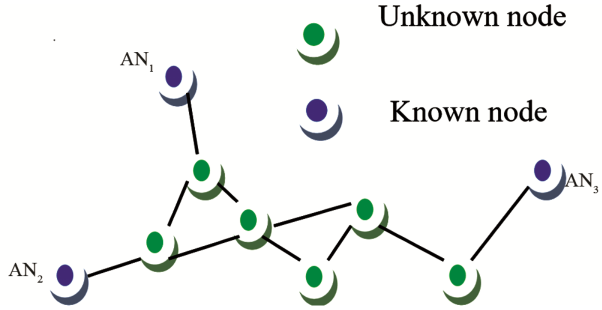

Fig. 11 — Localization using distance vector (DV) hop.

In this manner an object attached with a tag is identified. Figure 15 shows indoor positioning using RFID for tracking data[67].

Figure 16 represents magnetic positioning in indoor positioning system[68]. Smart phone's magnetic sensor's data is wirelessly used for the location of objects and people inside a building.

- **Magnetic positioning:** In this local variations are created by the metals inside the buildings in the magnetic field persisting in magnetic sensors. These magnetic variations are sensed and recorded by the smart phones for marking indoor locations.

3.2 Sensor fusion and filtering

Sensor fusion is used in a wide range of applications including industries, military, robot navigation, medical, or other commercial applications[31]. A novel improved model is used based on sensor data of individual sensors to get improved accuracy and reliability in sensor fusion using Eqs. (18)-(20) can either be done using measurement fusion or the state fusion. In the

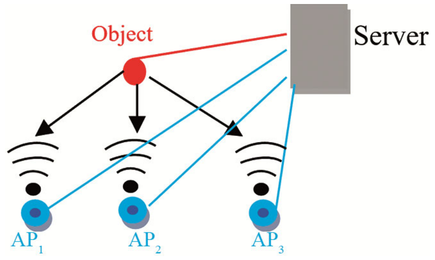

Fig. 12 — Indoor positioning using Wi-Fi and WLAN.

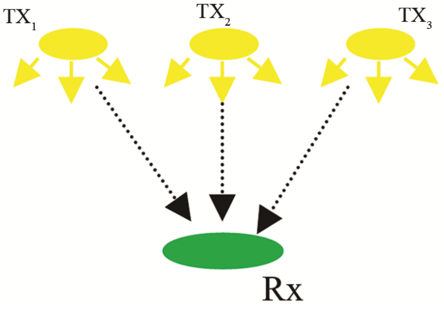

Fig. 13 — Indoor positioning using visible light communication.

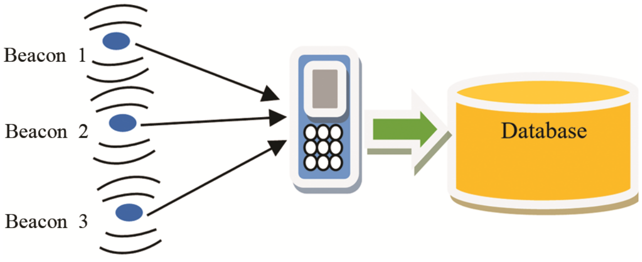

Fig. 14. — Indoor positioning using Bluetooth low energy (BLE) beacons.

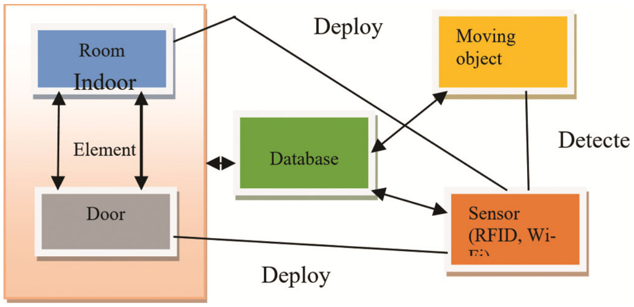

Fig. 15 — Indoor positioning using radio frequency identification (RFID).

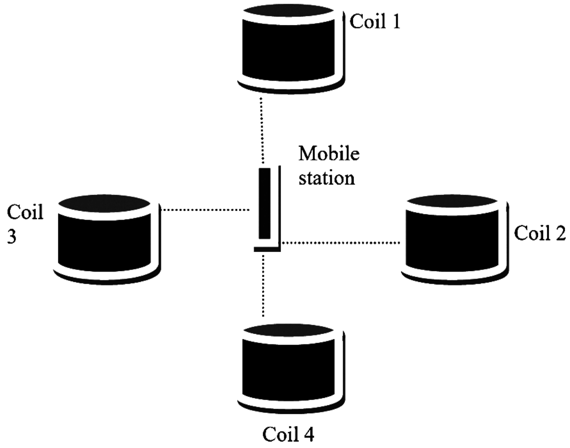

Fig. 16 — Indoor positioning using magnetic positioning.

measurement fusion, sensors' data measurements are merged into an observation vector and these measurements are combined using minimum mean square estimations. Then, in state fusion, the state vector is estimated.

$$y_{j+1} = G_j y_j + \tau_j u_j \qquad \dots (18)$$

Eq. (18) represents target's dynamics for identical sample rates of the sensors, where, $y_j$represents the state vector forj^{th} time, and u_j represents the state noise as:

$$E[u_j] = 0;\ E[u_j u_m^T] = P_j \delta_{jm}$$

Two sensor's measurements are computed as follows:

$$s_j^n = F_j^n y_j + v_j^n \ n = 1,2 \qquad \dots (19)$$

where, s_j^n is the measurement of n^{th} sensor at j^{th} time and v_j^n is the measurement of the noise sequences which are mutually independent, white, zero-mean with C_j^n as covariance in Eqs. (19) and (20).

$$E[v_j^n] = 0;\ E[v_j^n v_m^{nT}] = C_j^n \delta_{jm};\ C_j = \begin{bmatrix} C_j^1 & 0 \\ 0 & C_j^2 \end{bmatrix};$$

where, C_j is the merged noise measurement.

$$E[v_j^1 v_m^{2T}] = E[v_j^2 v_m^{1T}] = 0 \qquad \dots (20)$$

Various techniques of sensor data fusion persists, but Kalman filtering technique is the most significant one which includes both types of the measuring techniques including state fusion and the measurement fusion[69–71].

A. Kalman filter (KF) Algorithm

In case of uncertainty in information for a dynamic system Kalman filter is a suitable choice. Such dynamic systems are changing their state continuously. There is no requirement of history, only previous state is sufficient while processing via Kalman filter and this makes it lightweight, power efficient and fast for real time applications. In this, state estimations are based on linear dynamical systems.Working of Kalman filter is based on 3 phases i.e. Predict, Measure and Update[21].

a) **Predict:** New state or position of the target is predicted from its previous state or position. Based on the information of previous position for time n, new position for time n+1 can be predicted as in Eq. (21):

$$\hat{y}_{n+1}^{-} = C\hat{y}_n + Dw_n \qquad \dots (21)$$

where, $\hat{y}_{n+1}^{-}$ represents predicted state vector and $\hat{y}_n$ represents previous position of state vector, and w_n is the model matrix representing the state space, C is the transition matrix and D is the control input which is optional.

Eq. (22) represents covariance matrix given by:

$$Q_{n+1}^{-} = CQ_nC^T + N \qquad \dots (22)$$

where, N is the noise covariance matrix, contributing towards overall uncertainty. Larger changes are observed in the Kalman Filter if the value of N is high and vice-versa.

b) **Measure:**Predicted position is compared with the sensor's readings for the prediction. Kalman gain G_{n+1} is computed which is given by the following Eq. (23):

$$G_{n+1} = Q_{n+1}^{-} U^T (UQ_{n+1}^{-} U^T + M)^{-1} \qquad \dots (23)$$

where, U represents the measurements which are updated by covariance matrix of the predicted error Q_{n+1}^{-}, and M represents noise covariance measurement which determines the amount of usage of measurement information.

c) Update: On the basis of the sensor's readings and predictions for the positions, the new position is updated accordingly. The updated value of state vector is given by Eq. (24):

$$\hat{y}_{n+1} = \hat{y}^{-}_{n+1} + G_{n+1}(m_{n+1} - U\hat{y}^{-}_{n+1}) \qquad \ldots (24)$$

where, m_{n+1} represents the sensor's measurements Eq. (25) represents updated covariance matrix given by:

$$Q_{n+1} = (1 - G_{n+1}U)Q^{-}_{n+1} \qquad \ldots (25)$$

In these conventional Kalman filters, uncertainities and nonlinearities in predictions persist. To overcome these drawbacks Extended Kalman Filters are needed as described in section B.

B. Extended Kalman filter (EKF)

In EKF, optimization is done in a least-mean-squares manner. It is used in case of non-linear predictions, as the estimated covariances and the mean are linearized. It is suitable for transition models. The linearity for observation as well as state transition model is not needed, they can be differentiable. The procedure for measurements using EKF is described[72].

The state transition vector and the measurement vector are given as Eqs. (26) and (27), respectively,

$$y_{n+1} = g(y_n, w_{n+1}) + e_{n+1} \qquad \ldots (26)$$

$$m_{n+1} = u(y_{n+1}) + f_{n+1} \qquad \ldots (27)$$

where, w_{n+1} is the control vector, e_{n+1} is the process noise, and f_{n+1} is the measurement noise. EKF consists of following steps.

c. Predict: Based on the previous state, prediction of the new state is made. The estimated state and the covariance are predicted as follows in Eqs. (28)-(29):

$$\hat{y}_{n+1|n} = g(\hat{y}_{n|n}, w_{n+1}) \qquad \ldots (28)$$

$$Q_{n+1|n} = C_{n+1}Q_{n|n}C^{T}_{n+1} + N_{n+1} \qquad \ldots (29)$$

d. Update: The predicted state is compared with the measured values and then the new positions are updated accordingly as computed in Eqs. (30)-(36), respectively.

Measurement residual vector:

$$\tilde{x}_{n+1} = m_{n+1} - q(\hat{y}_{n+1|n}) \qquad \ldots (30)$$

Residual covariance vector:

$$R_{n+1} = U_{n+1}Q_{n+1|n}U^{T}_{n+1} + S_{n+1} \qquad \ldots (31)$$

Kalman gain:

$$G_{n+1} = Q_{n+1|n}U^{T}_{n+1}R^{-1}_{n+1} \qquad \ldots (32)$$

Estimation of updated state is given as:

$$\hat{y}_{n+1|n+1} = \hat{y}_{n+1|n} + G_{n+1}\tilde{x}_{n+1} \qquad \ldots (33)$$

Estimation of updated covariance is given as:

$$Q_{n+1|n+1} = (I - G_{n+1}U_{n+1})Q_{n+1|n} \qquad \ldots (34)$$

State transition matrix is given as:

$$C_{n+1} = \left.\frac{\partial g}{\partial y}\right|_{\hat{y}_{n|n}, w_{n+1}} \qquad \ldots (35)$$

Observation matrix is given as:

$$C_{n+1} = \left.\frac{\partial u}{\partial y}\right|_{\hat{y}_{n+1|n}} \qquad \ldots (36)$$

where, e_{n+1} and f_{n+1} are multivariate Gaussian noises which are assumed to be zero with covariances as N_{n+1} and S_{n+1}, g function is used for computation of predicted state from previously estimated state, and u function used for predicted measurement from predicted state. EKF has been used to refine the target location's computational accuracy[73,74].

3.3 Recent trends and existing technologies

The limitations in conventional indoor positioning techniques like fluctuations in the RSSI, reduction in accuracy because of persistence of NLOS signal, and requirement of huge database and human efforts increases the requirement of AI for indoor positioning, in order to easily handle huge amounts of data for hospitals, shopping complexes, airports etc. Moreover, use of AI for indoor positioning enhances the adaptability for the changing environment, ensures easy handling of the multidimensional data and handles attenuation in noisy environments with the help of multidimensionality.

To get a better idea of suitability of various AI techniques according to the application for indoor positioning it is important to understand AI, ML, and DL techniques.

- **Artificial Intelligence (AI):** It is the machine's ability to imitate the human mind's capabilities.
- **Machine Learning (ML):** It includes the techniques, from which patterns can be learned from the data without being programmed explicitly.
- **Deep Learning (DL):** In this, ML algorithms are included, from which there is a capability of automatic feature extraction from the data.

Hybrid Multimodal Deep Neural Network (MDNN) localisation system, MMLOC has been used for sensor fusion based smartphone location tracking. Innertial sensors (magnetometer, gyroscope, accelerometer) and RSS data are used as input. This input data has been collected using smart phone's android application. After preprocessing of the collected data, MDNN is used for data fusion of features of pedestrian dead reckoning (PDR) on the basis of innertial sensors data extracted from Recurrent Neural Network (RNN) and location estimation features with the help of Wi-Fi fingerprints by Deep Neural Network (DNN). In this manner sensor data fusion has been automatized by making it data driven unlike in conventional fusion processes (Kalman Filter and Particle Filter), as learning process of data processing models has been made automatic instead of requirement of hand picked features. As a result, 1.9 m median error has been achieved using MM-LOC with the ease of deployment because of its automatic learning capability from the data[75].

B. ML-Supervised Learning

Supervised Learning method is one of the widely used technique, where the data is always labelled. Between input data and labels, the mapping function is grasped. In this, for input with a specified label of the object, the algorithm is trained until it becomes capable of correctly determining the relationship between the input data and the output labels. Supervised Learning is carried out primarily in following two steps to compute the model accuracy.

- **Training:** System is provided with a labelled dataset that trains it to distinguish different inputs with their respective outputs.
- **Testing:** Trained system is tested based on its performance accuracy for the unlabelled data.

Based on the generation of results supervised learning is categorised as:

- **Classification:** On the basis of labeled data used for training inputs are sorted into their respective classes by the classification algorithms, which can be in the form of binary classifications like marking documents as checked or unchecked for easy classification, or feature recognitions like classification of food items as vegetables, fruits, pulses, cereals, juices, and shakes.
- **Regression:** In this model is expected to produce numerical relationship between input and output data e.g. determination of number of customers with different age groups willing to purchase certain products.

Supervised Machine Learning (SML) is generally used for the data that can be related according to human judgement. It is suitable for Support Vector Machine (SVM), Random Forests Regression (RFR), neural networks (NN), linear regression (LR), Decision Tree Regression (DTR), Bayseian logic, logistic regression, similarity learning, and linear discriminant analysis algorithms. Before the choice of the respective supervised learning algorithm, biasness, accuracy, heterogeneity, linearity, model complexity, redundancy, and variance must be considered.

SML based device free indoor positioning for Internet of Things (IoT) applications using received signal strength indicator (RSSI) has been implemented using Python 3 via Jupiter Notebook[76]. In this, RSSI values are collected from sensor nodes which are used to train SML algorithms: RFR, DTR, Polynomial Regression (PR), LR, and SVM. These trained SML algorithms are used to test new data.

C. ML-Unsupervised Learning

In unsupervised machine learning (UML), patterns are detected on the basis of unlabelled data. Conclusions are made on the basis of DL techniques. UML is based on:

- **Clustering:** Data is grouped based on common features e.g. grouping of flowers on the basis of their similarities.
- **Association:** Relationship between portions of data is discovered, e.g. customers willing to purchase product A, may like product B.
- **Dimensionality reduction:** In this, high dimensional data is projected into low dimensional space e.g. separation of mixed signal into its basic components for analysing it properly.

K-means clustering, and the *Apriori* are the algorithms based on unsupervised learning. For dealing with new information unsupervised learning is the most suitable approach.

UML approach known as "expectation maximization for Gaussian mixture models" has been applied to classify line-of-sight (LOS) and non-line-of-sight (NLOS) conditions of propagation for ultra-wideband positioning system. This enhances accuracy in detecting NLOS components because of the absence of training phase. The detected NLOS components can be discarded from the positioning algorithm to refine its accuracy[26].

D. ML-Semi Supervised Learning

In semi supervised machine learning (SSML), some part of data is unlabelled, whereas other part of data is labelled using special techniques. Correlations are established between data points and after that determined labels are used for marking those data points. In this way, the entire model gets trained. In this type of ML at least 25.0% of data is labelled and generally provides accurate results, so it is applicable to solve real world problems. It is used for facial recognition, natural language processing, data creation, audio and video manipulation[77].

Device free indoor localization based on deep convolutional generative adversarial network (DCGAN) – SSML has been used to acquire better performance in indoor localization. Since it uses comparatively less labeled data and more unlabeled data than SML algorithms. So, there is reduction in cost of labeling unlabeled data. In this system, wireless channel state information (CSI) data (both labeled and un-labeled) has been used directly to train model using binary cross–entropy loss function and adam optimizer. As a result, maximum accuracy of 87.84 has been achieved for 6400 labeled samples of CSI[78].

E. ML-Reinforcement Learning

ML based Reinforcement Learning (RL) is based on learning by self interpretation on the basis of rewards and penalties on its behaviour. It is desired to get maximum rewards and minimum penalties in this type of ML. Q-Learning and Model based value estimation are the algorithms based on Reinforcement learning.

Particle Filter (PF) based RL has been used for autonomous-reliable wireless indoor positioning. Fusion of IMUs, predicted zone, coarse-grained floor plan information, and radio-based ranges have been implemented in PF for stable and accurate real time indoor positioning. RL has been used in PF to ensure reliability of the system against localisation failures like robot kidnapping issue. In this system, RL is used as tracking algorithm and is modeled as learner agent (LA) using Q-learning approach. In this, evaluation of actions performed during particular state is reflected in the form of quick reward and penalty. This helps LA to learn optimal behaviour. As a result, faster convergence of this localisation system with failure recovery has been achieved[79].

F. Overfitting

This problem generally persists when the model generally performs well only during training but not during testing. It generally occurs when there is long training, insufficient training data, and model is complex.

In visible light communication (VLC) based indoor positioning (IP), reflected signals and noise are considered as compared to traditional IP solutions. The improvement in visible light based indoor positioning has been made using classification and regression processes applied after cross validation (CV) technique for comparing accuracy of each ML algorithm. The combination of signal pre-processing (for filtering noise and elimination of low intensity reflective signals have been used to reduce noise sensitivity) and two ML based algorithms: classification and regression functions have been used. Classification reduces computational time. Regression helps in determination of estimated location of photo-detecter (PD). It consists of offline and online phases. Received Signal Strength (RSS) data is collected from all fingerprints along with noise reduction, area division and training process in offline mode. In online mode, gathering of online data from the current location of PD along with noise reduction, area reduction, and current location prediction are accomplished. This not only resulted in reliability varification and overfitting avoidance but also provided selection optimal algorithm to achieve high accuracy in positioning within optimal requirement of computational time[80].

G. ML-Pipeline

It includes ML workflow in which data is enabled to get correlated and transformed into the model for its analysis to get the output.

Figure 17 represents ML-Pipeline[81] and its steps are as:

- Data Collection: Data is collected to train the ML model.
- Data Pre-processing: Data is cleaned and formatted.
- Feature Engineering: Features are extracted for providing relevant data as input using DL.

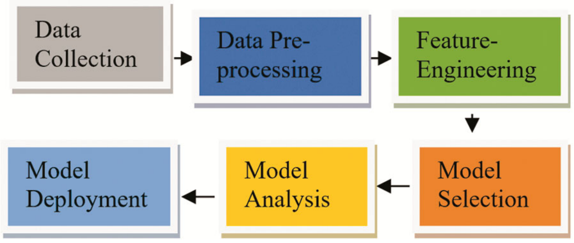

Fig. 17 — ML-pipeline.

- Model Selection: Various models are evaluated to select the best model for the required application.
- Model Analysis: Predictions are analysed.
- Model Deployment: Model is tested in the real world scenario.

H. Existing Technologies

Accuracy is the main concern for indoor positioning, which can be improved by using the combination of sensor fusion and AI[21], [82]. In[21], measurements from 3 sensors including gyroscope, accelerometer, and magnetometer are fused using kalman filtering to remove noise, and to estimate drift free orientation for accurate positioning, for dealing with the external environment where adaption to the changing conditions are needed, artificial neural network (ANN) based learning to prediction model has been used for improving accuracy in predictions with error factor of 0.020, and RMSE of 2.38.

The localisation using fingerprinting requires high storage and its computational complexity is large, as high dimensional data exists which results in highly time consuming measurements, requiring high power consumption. To mitigate these challenges, fingerprinting in[83] uses RSS path-loss model in offline mode for constructing initial radio-map, along with crowd-sourcing for the updation of fingerprinting in online phase using ML.

To improve the efficiency of indoor logistic distribution, an intelligent wheeled actuator is designed and implemented using sensor fusion which is composed of intelligent elevators, integrated logistic actuator, and remote logistics centre. The realisation of cross-floor route planning and distribution using simultaneous localisation and mapping method based on wireless communication network has been made. A*+GAHC algorithm has been proposed to improve distribution efficiency with a 22.70% reduction in total time cost when compared with other algorithms[23].

In[84], an application (Blind MuseumTourer) for Android smart-phones has been proposed which is to assist blind or visually impaired persons and museum pupils to navigate inside museums and also to airports, hospitals, shopping malls, offices etc. For accurate positioning combination inertial dead reckoning and proximity has been used. Only specific classification models can be trained by using traditional ML models, so its deployment and management on the cloud database is difficult, and it is hard to train multi-classification models using few samples of fingerprinting.

In[85], these problems are solved by using a binary classification model based on differences of the samples, in which pairs of the raw fingerprint are divided into positive and negative samples on the basis of distance of each pair[85]. For testing of the performance open-source *UJIndoorLoc* dataset has been used. According to the results, better performance has been observed in comparison with NN and other binary models for classification. With the evolution of Internet of Things (IoT), there is a requirement of sensor based indoor positioning and tracking, and for that the performance is enhanced by improvement in the identification of the type of surrounding environment which improves the accuracy. In [30] a two-stage cascaded ML approach is proposed. First stage is the identification of the type of environment using ML. Second stage is the identification of the most suitable selection of radio frequency (RF) approaches and their combination using k-nearest neighbor ML algorithm, for real dataset obtained from practical approaches of measurements of RF signal in the indoor environment. The obtained results show that there is improvement in accuracy from 50.0% to 70.0%. Table 2 shows the various algorithms for indoor positioning (with and without ML technology). In[86], accurate 3D-position in vertical as well as horizontal direction of pedestrians is estimated in indoor and outdoor environments without using GPS. This estimation is based on the integrated ankle sensing device consisting of gyroscope, barometer, accelerometer and magnetometer. Vertical position is determined using sensor fusion of acceleration data obtained from accelerometer, angular velocity data from gyroscope, and height data measurements from barometer. Horizontal position is estimated by introduction of vertical variable in stride length model along with multi-sensor-fusion method, i.e. based on multiplicative extended Kalman filter (MEKF) heading angle estimation using pedestrian dead reckoning (PDR) to improve the positioning accuracy. This results in significant reduction of errors.

It is quite difficult to navigate in the indoor environment based on microwave systems for narrow corridors due multipath reflections and this result in an increase in positioning errors. To resolve this, in [87] an alternative approach for indoor positioning has been proposed, in which multimodal sensor fusion of secondary data of radar and odometer with ultrasonic sensor has been done to assist service robot to perform well for positioning in the indoor environment of hospitals, or university and office buildings.

The localization using fingerprinting requires high storage and its computational complexity is large, as high dimensional data exists which results in highly time consuming measurements, requiring high power consumption. To mitigate these challenges, fingerprinting in [83] uses RSS path-loss model in offline mode for constructing initial radio-map, along with crowd-sourcing for updating fingerprinting data in online phase using ML.

For localizing moving residents and to track their activities like walking, sleeping, and standing in the indoor environment, in [88] sensor fusion algorithm based on the particle filter has been proposed to fuse data obtained from IMU (wearable sensor) and PIR (environmental sensor) to get higher accuracy. For human activity recognition, heading and velocity estimation, angular rate and acceleration data have been used from the IMU sensor.

Table 3 shows indoor positioning using different DL algorithms. Table 4 shows various types of sensors with the description of their functionality required for indoor positioning.

3.4 Deep Learning over Conventional indoor positioning system

Due to unstable received signal strength (RSS), radio frequency (RF) based conventional localization techniques are complex to be implemented in the indoor environment whereas signal strength of geomagnetic sensor is more stable than RF RSS. So, to recognize time varying sequences of sensor's data for tracking object movement in the indoor space, recurrent neural network (RNN) based Deep Learning

Table 2— Indoor Positioning with and without ML

	Reference No.	Algorithm	Remarks
With ML	21	Artificial Neural Network (ANN)-Feed Forward Back Propagation Neural Network (FFBPNN)	It is used as a learning to prediction model which helps the system to adapt in the changing environment and removes noise.
	30	k-nearest neighbour	Two-stage cascaded ML approach is proposed. First stage is the identification of the type of environment using ML. Second stage is the identification of the most suitable selection of radio frequency (RF) approaches and their combination.
	73	Modified k-nearest neighbour	For calculation of current location of the pedestrian
Without ML	87	Multimodal sensor fusion of secondary data of radar and odometer with ultrasonic sensor	It assists service robots to perform well for positioning in narrow corridors of the indoor environment of hospitals, or university and office buildings.
	99	Application of current mainstream attitude and heading reference system (AHRS) algorithm	The directional accuracy has been improved as attitude related errors can be compensated continuously.
	88	Sensor fusion of IMU and PIR based on the particle filter	Higher accuracy is obtained for human activity recognition

Table 3 — Indoor Positioning Using Deep Learning Methods

Reference No.	Algorithm	Remarks
27	Convolutional neural network-Long Short-Term Memory (CNN-LSTM)	CNN-LSTM is used for Ultra-Wide-Band (UWB) non-line-of sight (NLOS)/ line-of-sight (LOS) classification. UWB-Channel impulse response (CIR) data is the input to CNN –LSTM. Automatic extraction and exploration of features is done using CNN. Classification of CNN outputs is done using LSTM.
103	Deep Reinforcement Learning	Indoor Navigation in a real environment with the ability to handle 3-D obstacles is based on an autonomous self learning robot in which sensor fusion of RGB-D camera and 2-D laser scanner data is used.
37	Recurrent convolutional neural network (RCNN)	For robot localisation, RCNN is used for the fusion of inertial and laser data for improving accuracy and robustness.
100	CNN	For indoor operating ground robots, CNN is used to fuse depth and vision measurements from LiDAR and camera. This makes it autonomous and resistant to corruption of sensors' data.
73	CNN	CNN is used for recognition of indoor scenes that helps in reduction of positioning errors which results in identification of specific floors and reduces the dependence of device because of built-database.
104	Deep Neural Network (DNN)	Estimation of location by recognition of magnetic sequence patterns.

Table 4 — Sensors requirements and their functions for indoor positioning

Sensor	Function
Passive Infrared Sensor (PIR)	It consists of a pair of pyroelectric sensors for the detection of heat energy from the surroundings. Differential signal between the pair of pyroelectric sensors is changed, when the person enters near PIR, and in this way PIR starts operating.
Accelerometer	It is used to measure and sense various acceleration forces like static (continuous gravitational force), or dynamic (due to motion or vibration). In this vibrations created by the body are absorbed and used for knowing the body's orientation.
Magnetometer	It is used for measuring magnetic fields with respect to magnetic orientation and strength. It can be of various types, like a compass (consisting of a magnetic needle which will align itself in north along with earth's magnetic field) or coil magnetometers (based on electromagnetic induction). It is based on the principle that the sum of forces acting on it is zero, e.g. in compass, its weight is cancelled by earth's magnetic force acting on it.
Gyroscope	It measures angular velocity along various orientations (pitch, roll, and yaw). It is based on the conservation of angular momentum principle, in which there is constant spinning unless external torque is applied.
Barometer	It is used to measure atmospheric pressure and hence can be used to determine height as there is variation in atmospheric pressure with varying altitudes.
Lidar	It is a kind of depth sensor in which pulsed light is emitted by the laser, which is bounced back by the objects in the surrounding environment and the time taken by the light to return back to the sensor is used for calculating the distance travelled by it.
Kinect RGB-D sensor	It is used for detection of the motion and creation of physical image on the screen using multi-array microphone, depth sensor, and RGB coloured video camera

(DL) approach is appropriate as RNN has the capability of memorizing contiguously varying patterns of sequence of geomagnetic vector. A large infrastructure is needed for positioning with conventional techniques than DL based approach. More localization accuracy is provided by DL based geomagnetic sensor approach than conventional techniques[89].

Although, supervised learning based approach provides low complexity with high accuracy. But in such systems large amount of labeled data is required for offline training which is very costly. The problem of missing and unlabelled data can be solved with supervised deep neural network (DNN) based DL approach. DNN can be trained on mixed dataset (real and fake) using weighting techniques, for improving prediction of location and to avoid overfitting[90].

3.5 Issues and challenges in indoor positioning

Indoor Positioning System lacks accuracy because of various technical and non-technical challenges. Indoor maps are not covered properly due to privacy issues and there is lack of technical system for ensuring privacy protection of data. There is still a requirement of reliable and the accurate indoor positioning system which can withstand the changing environment, non-line-of sight (NLOS) and multipath propagation. Multi-sensor fusion can provide the solution for indoor localization, but it necessitates the miniaturization of devices for compatibility with size of mobile. Storage of indoor maps is the quite challenging because of security concerns [91]. A large amount of data is acquired from fusion based technologies that increases computational cost which is needed to be reduced without compromising with accuracy. Fusion efficiency can be improved further by considering accuracy and diversity of each network[31].

AI techniques for indoor positioning are data dependent. So, there is a need of the system for prediction and training of data that is not dependent on hardware of devices. There is lack of variability using ML techniques because of requirement of historical data still persists but problem arises with changing environment and varying situations. So, an adaptive system is required that can capture and handle the variations in the environment and work accordingly [22].

3.6 Comparison with existing survey articles

Existing literatures based on indoor positioning have been surveyed and it has been analyzed that[22] describes the ML approaches to overcome challenges persisting in conventional techniques for indoor positioning,[31] is about survey of fusion based indoor positioning technologies. In[92] various techniques of indoor positioning have been discussed with applications and special focus on visual/depth sensors. These surveys are primarily focused on a single domain such as fusion based or ML based or visual/depth based technologies while in this paper all the techniques starting from evolution of IPS including conventional to recent state-of-the-art techniques are covered. Further, this paper describes the need of indoor positioning, conventional techniques, and its drawbacks. Sensor fusion and filtering to overcome the drawbacks in conventional techniques and further enhancement in accuracy and adaptability using AI and other hybrid approaches are also covered. Finally, importance of deep learning over conventional IPS, issues and challenges in current IPS, and future directions have also been provided for better understanding and implementation.

4 Conclusion

In this paper, the idea about the need of indoor navigation hasbeen described. So, the methods to improve indoor positioning as per the existing literature and the related technologies have been discussed. It has been inferred that AI along with sensor fusion has not only significantly boosted the accuracy and reliability of IPS but also resulted in reducing human effort in maintaining dimensionality of data according to the requirements, management of large databases, and reducing NLOS and other multipath related errors. Moreover, adaptation of models according to the changing environment has been maintained using AI, sensor fusion and other hybrid technologies. DL has resulted in autonomous IPS which is resistant to sensor's data corruption, and posseses an ability to handle 3-D hurdles. But there is lack of data variability, i.e., there is a dependence on historical data.

So, in the future with advanced communication and infrastructure, IoT based systems can be linked with advanced 5G technology for automatic maintenance of historical data.

Acknowledgment

Authors would like to acknowledge the Director of UIET, Prof. J.K. Goswamy, for providing the lab facility to carry out the research work. First author is also thankful to Panjab University, Chandigarh for providing research fellowship

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