Location of Things (LoT): A Review and Taxonomy of Sensors Localization in IoT Infrastructure

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***Abstract*—Internet of Things (IoT) is a novel design paradigm, intended as a network of billions to trillions of tiny sensors communicating with each other to offer innovative solutions to real time problems. These sensors form a network named as Wireless Sensor Networks (WSN) to monitor physical environment and disseminate collected data back to the base station through multiple hops. WSN has the capability to collect and report data for a specific application. The location information plays an important role for various wireless sensor network applications. A majority of the applications are related to location based services (LBS). The development of sensor technology, processing techniques and communication systems give rise to a development of the smart sensor for the adaptive and innovative application. So a single localization technique is not adequate for all application. In this paper, a recent extensive analysis of localization techniques and hierarchical taxonomy and their applications in the different context is presented. This taxonomy of the localization technique is classified based on presence of offline training in localization namely self determining and training dependent approaches. Finally, various open research issue related to localization schemes for IoT are compared and proposed various directions for future research.**

***Index Terms*—Wireless Sensor Network (WSN), Internet of Things (IoT), Localization, LMFF, RBFM, SDP, MDS, Fingerprinting**

I. INTRODUCTION

INTERNET of Things is a network of sensor and actuator nodes called 'things'. 'Things' refers to device or sensors that sense physical world signals and records it in digital forms [1]. Location-based services (LBS) in variety of recent applications including military [2], e-Health, environment monitoring, IoT, cyber-physical systems, home office automation [3] [4], weather forecasting, early warning and rescue operation etc. Global Positioning System (GPS) can be the solution to all of these services. But GPS uses high hardware cost, high power consumption and poor performance in indoor environment. So a large number or researches are conducted to optimise the location based services. Localization is the process of ascertaining the location of unknown sensor nodes in network with the help of some reference nodes called anchors or beacon nodes. The reference nodes obtain location information with inbuilt GPS module or manual deployment. Localization is a two step process of distance measurement between sensor nodes followed by calculation based on measured distances.

Various type of classification of localization algorithms has been proposed such as Range Based algorithms calculate location information from range based measurement techniques like Received Signal Strength (RSS) [5], Time of Arrival (ToA) [6], Time Difference of Arrival (TDoA) [7] and Angle of Arrival (AoA) [8]. Range free algorithms calculate the location information from the connectivity information. Some physical measurement based Localization schemes are classified as Coarse-Grained and Fine-Grained as illustrated in Fig. 1. Another way of classification is based on cooperative

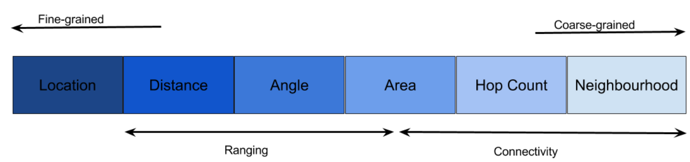

Fig. 1. Physical measurements used in localization schemes

and non cooperative. In cooperative method the neighbouring sensor node collectively process information to find location whereas in non cooperative method they process information individually. Based on processing point, the algorithms can be network centric positionings like Centralized scheme or self-positioning like Distributed scheme.

There are plenty of literature showing various methods and algorithms for localization. Most literature do not have proper classification of the problems in localization and recent advancements. Few literature concentrate on mobility [27] [28] [29] and other concentrate on processing aspects of algorithms [10] [37] [35].

The objective of this paper is to compare the research works related to localization and classify them in a framework applicable to IoT infrastructure and provide the taxonomy. Acronym and definitions are provided in the Table. I.

Many literature survey have been conducted on localization methods. The comparative analysis of the published survey work is illustrated in Table. II. Costa et. al. [9] have presented a set of Multi-Dimensional Scaling (MDS) algorithms and specified centralized and distributed methods for localization. A generalized survey of localization on stationary wireless sensor network is conducted by Mao et. al. [10] [15]. Gwo Yu et. al. [11] classified localization algorithms based on Multi-Dimensional Scaling (MDS) in the hierarchical network. The work only concentrates on accuracy and comparisons of various MDS schemes. Santos et. al. [12] explained the process and computational steps involved in the process of

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TABLE I
LIST OF ACRONYMS AND CORRESPONDING DEFINATIONS

Acronym	Defination	Acronym	Defination
3D-MALS)	Three Dimensional Multi-power Area Localization Scheme	LMAT	Localization Algorithm with a Mobile Anchor node based on Trilateration
3DUL	Three-Dimensional Underwater Localization	LMCS	Localization with a Mobile Beacon based on Compressive Sensing
3DVFDPP	Three Dimensional Virtual Force Dynamic Path Planning	LMFF	Levenberg-Marquardt Feed- forward
AAL	AUV-Aided Localization	LSHL	Large-Scale Hierarchical Localization
ABC	Assumption-Based Coordinates	LSLS	Large-Scale Localization Scheme
ADMM	Alternating Direction Method of Multipliers	LWUPLM	Localization With Unknown Path-Loss Model
ADO	Arrival and Departure Overlap	MACL	Mobile Anchor Node Centroid localization
AFL	Anchor Free Localization	MALS	Mobile Assisted Localization by Stitching
ALS	Area-based Localization Scheme	MARB	Moving Aerial Robotic Beacon
ANN	Artificial Neural Network	MASL	Motion Aware Self Localization
APT	Accurate Pedestrian Tracking	MBAL	Mobile Beacon Assisted Localization
BR	Bayesian Regularization	MBL	Mobile Beacon Localization
BRF-BTG	BReadth-First- Back-Tracking Greedy	MBL (NDC)	Mobile Beacon Assisted localization algorithm based on Network Density Clustering
BRL	Bayesian Ranging Based Method	MCL	Monte Carlo Localization
BSR	Beacon Signal Ring	MDP	Markov Decision Process
C-ML	Cognitive Maximum Likelihood	MLP	Multi Layer Perceptron
CAPS	Cell-ID Aided Positioning System	MMDP	Multiagent Markov Decision process
CL	Collaborative Localization	MSL	Multiple Source Localization
DECPOMDP	Decentralized Partially Observable Markov Decision Process	MSL	Multi-Stage Localization
DESR	Dual Embedding Spectral Regression	NAL	Nine Anchor Localization
DETL	Detachable Elevator Transceiver Localization	PA	Peer Assisted
DNRL	Dive and Rise Localization	PD	Probability Distribution
DOL	Distributed Online Localization	PI	Perpendicular Intersection
DREAMS	Deterministic Beacon Mobility Scheduling	PL	Passive Localization
DS theory	Dempster-Shafer theory	POMDP	Partially Observable Markov Decesion Process
DTN	Dynamic Triangular Network	PWF	Peak based Wi-Fi Fingerprinting
DV-ARND	Distance Vector-Adaptive Regulated Neighborhood Distance	RAA	Range-free Aerial Anchor
DV-Hop	Distance Vector Hop	RAPS	Rate Adaptive Positioning System
DWKNN	Distance Weighted k-Nearest Neighbors	RBFN	Radial Basis Function Network
ECHO	Extended Computation scHeme of cOordinate	RD	Random Direction
ECM	Expectation Conditional Maximization	RNST	Reference Node Selection based Triangulation
EEL	Energy Efficient Localization	RODL	Robust Distributed Network Localization
EnLoc	Energy-efficient localization	RP (LM)	Resilient Back-propagation (Levenberg-Marquardt)
FAL	Five Anchor Localization	RW	Random Walk
FF	Feed-forward	RWP	Random Way Point
fGn	Fractional Gaussian Noise	SCG	Scaled Conjugate Gradient
GAC	Gps Accelerometer Compass	SG	Stochastic Game
GD	Gradient Descent	SLMP	Scalable Localization with Mobility Prediction
GM	Group Mobility	SLNN	Source Localization with Nuclear Norm
GMAN	Group of Mobile Anchor Nodes	SOCP	Second Order Cone Programming
GR	Generalized Regression	SPNP	Six Possible Next Positions
HiRLoc	High-Resolution robust Localization	UPS	Underwater Positioning Scheme
HL	Hexahedral Localization	USP	Underwater Sensor Positioning
HL	Hyperbola-based Localization	VBT	Visibility Binary Tree
HSL	Half Symmetric Lens	VC	Virtual Compass
LCB	Localizable Collaborative Body	WCL	Weighted Centroid Localization
LDB	Localization with Directional Beacons	WPS	Wide Coverage Positioning
LLSE	Linear Least Square Estimation	ZCL	ZigBee-based collaborative localization

localization. They consider only three localization algorithms namely directionality based algorithms, terrain and hop-terrain and compared their benefits, the source of error and accuracy. Mobile WSNs are analyzed and classified by Amundson et. al. [13]. This paper discussed the benefit of mobility, the difference within static and mobile wireless sensor network, the architecture of mobile WSN, localization steps and effect. Faheem et. al. [14] gave an overview of data-dissemination in mobile sink environment. They described data dissemination methods based on mobility model, mobile sink routing and application type. Pal et. al. [16] proposed a classification of localization algorithms and shown factors that affect the process. Kulaib et. al. [17] presented a distance-based localization algorithm review. They took ten algorithms that have distinct characteristic and classified the algorithms as centralized, distributed and distributed-centralized. It shows that centralized localization algorithms produce better location estimation than distributed and distributed-centralized algorithms. Li et. al. [18] classified a set of localization and tracking algorithms based on centroid algorithm, trilateration algorithm and maximum likelihood estimation. Cheng et. al. [19] explained target localization as an energy-based method and investigated node self-localization methods. A discussion on challenges in non-line-of-sight, node selection criteria, scheduling the sensor node and evaluation of localization criteria are also conducted. Stone et. al. [20] provided a three-tier grading method in that first they sort algorithm based on distributed, distributed-centralized and centralized and then classified using protocol techniques. Alrajeh et. al. [21] classified and analyzed localization methods as range-based and range-free. Dong et. al. [22] conducted a comparative survey of mobility issue and medium access control (MAC) protocols of WSN. Han et. al. [23] [36] analyzed approaches based on static nodes, mobile nodes, range-based and range-free. Mesmoudi et. al. [24] have evaluated localization strategies as range-based, range-free and hybrid methods. Patel et. al. [25] have studied localization approaches based on different range measurement techniques. Kuriakose et. al. [26] ranked localization algorithms based on the properties anchor node in the network. Tunca et. al. [27] surveyed based on sink mobility in WSN. Yu Gu et. al. [28] conducted a comprehensive review on sink mobility management. Mistry et. al. [29] explained localization based

TABLE II
COMPARISION OF SURVEY WORKS FOR LOCALIZATION TECHNOLOGY

Survey Works	Focus	Static Coverage	Mobility Coverage	Fingerprint Based	Probability Estimation	Machine Learning	Remarks
J.A. Costa 2006 [9]	Localization	Extensive	No	No	No	No	Fine-grained based on anchor properties and processing information covered.
G.Mao 2007 [10]	Localization	Extensive	No	No	No	No	Comprehensive organizations of static localization designs
G.Yu 2007 [11]	Localization	Extensive	No	No	No	No	Range based and range-free (Hybrid and Full) methods reported
F. Santos 2008 [12]	Localization	Limited	Extensive	No	No	No	Categorized different schemes based on coordination, measurement, and estimation
I. Amudson 2009 [13]	Localization	No	Specific	No	No	No	Features on MWSNs but poor algorithmic specifications
Y. Faheem 2009 [14]	Data Dissemination	Yes	Specific	No	No	No	Organizations on data distribution procedures of mobile sink
G. Mao 2009 [15]	Localization	Extensive	No	No	No	No	Static localization methods only explained
A. Pal 2010 [16]	Localization	Extensive	No	No	No	No	Classification of Static Localization
A.R Kulaib 2011 [17]	Localization	Static Coverage	No	No	No	No	Distributed ,distributed-centralized or centralized distance based approach
X.Li 2011 [18]	Localization	Extensive	No	No	No	No	Classification based on single and multi-hop algorithms.
L. Cheng 2012 [19]	Localization	Extensive	No	No	No	No	Classified algorithms based on range,number of anchors and processing types.
K. Stone 2012 [20]	Localization	MDS Based	No	No	No	No	Based on different types of Multi-dimensional Scaling approaches.
N.A. Alrajeh 2013 [21]	Localization	Extensive range based	Extensive	No	No	No	Mobility of anchor and sensor node is discussed with extensive mobility model
Q. Dong 2013 [22]	MAC Protocol	Extensive	Extensive	No	No	No	Survey on Medium Access Protocols.
G. Han 2013 [23]	Localization	Extensive	Extensive	No	No	No	Mobility of Nodes is considered for localization.
A. Mesmoudi 2013 [24]	Localization	Extensive	Limited	No	No	No	Distinctive Classification with details of the attributes.
R. Patel 2014 [25]	Localization	Limited	No	No	No	No	Range free localization , no classification
J. Kuriakose 2014 [26]	Localization	Limited	No	No	No	No	RSSI based localization Schemes.
C. Tunca 2014 [27]	Sink Routing	Extensive	Extensive	No	No	No	Comprehensive comparison of routing protocols for mobile sink nodes.
Y. Gu 2014 [28]	Sink Mobility	Extensive	Extensive	No	No	No	Classification based on sink mobility management.
R.P. Mistry 2015 [29]	Localization	Extensive	Extensive	No	No	No	Classification based on Range Measurement.
A. Alsheikh [30]	Localization	Limited	Limited	No	Yes	No	Markov decesion Model for Localization in WSN
A.K.M. Hossain 2015 [31]	Localization	Limited	Limited	Yes	No	No	Calibration free indoor Positioning
S. He 2016 [32]	Localization	Extensive	Limited	Yes	No	No	Wi-Fi Fingerprint based Indoor Localization
Q.D. Vo 2016 [33]	Localization	Extensive	Limited	Yes	No	No	Fingerprint based outdoor Localization
S.K. Gharghan 2016 [34]	Localization	Extensive	No	No	No	Yes	Comparative study of Machine Learning based Estimatiors for Localization.
T. Chowdhury 2016 [35]	Localization	Extensive	Extensive	No	no	No	Discusses algorithms from static and mobility concept
G. Han 2016 [36]	Localization	Limited	Extensive	no	no	No	Discusses Mobile anchor node assisted Localization
Our work	Localization	Extensive	Extensive	Extensive	Extensive	Extensive	Categorize and Discuss algorithms for IoT Infrastructure

on RSSI measurement and classified different algorithms to reduce localization error and improve accuracy.

Alsheikh et. al. [30] reviewed the localization methods to address data transfer, topology formulation, power optimization, resource optimization, sensing coverage, object discovery and security challenges. Hossain et. al. [31] reviewed emerging fingerprint based localization in indoor positioning system. Suining He et. al. [32] conducted survey on recent advancement in fingerprint based localizations and presented the effectiveness of temporal or spatial signal patterns. Q. D. Vo et. al. [33] conducted a classification of existing fingerprint-based localization strategies which intelligently sense and match different parameters from the environment to identify the location. Gharghan et. al. [34] examined different machine learning based approach for localization and the influence of anchor node density on localization accuracy in the indoor environment. Chowdhury et. al. [35] classified localization techniques based on the algorithms type, comparative analysis, and application.

As discussed, the majority of survey is only based on either range-based and range-free [11] [19] [25] [29] or Centralized and Distributed [9] [17] [35]. Majority of the localization issues together are not covered by the existing papers each paper presents some aspect. [34] [33] [32] [31]. In this survey paper the parameter definition, classification of algorithms, comparative analysis of available algorithms are reviewed and summarised along with future research direction. The proposed survey paper is broadly compared to the other review papers presented in the literature and shown in Table II. The contributions of this survey paper is to provide an insight and review of localization technology targeting to IoT infrastructure. The rest of the paper is organised as follows: The localization problem in IoT infrastructure is presented in Sec II. The classification of localization algorithms are presented in Section III to X, In Section XI practical application and further research directions is discussed. Finally, Section XII presents the concluding remarks followed by references.

II. LOCALIZATION PROBLEM IN IOT INFRASTRUCTURE

Internet of things conceptualised a big connectivity model where all devices and services from all the places connected to the internet all time. The 'things' of IoT are heterogenous devices consists of sensors and actuators. The sensor senses signals from environment and the actuator act on environment. The IoT opens an important dimension called 'Location of Things' (LoT) where things get geographical position information. There are billions of 'things' in IoT and continuously adding. To organise this big data from huge amount of heterogenous devices the location information plays an important role. IoT pulls data from huge devices, filter out and organise them by means of location information. Hence location acts as a search engine for organising big data and devices.

The localization principle developed 20 years back with the development of GPS for military application further it is commercialised. Currently all device connected to internet uses location information e.g. Google Map, Uber, Waze, Foursquare

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etc. Hence the location based services (LBS) comes into play as a paradigm shift from traditional localization i.e GPS. GPS is just a subset of LBS since it cannot localize 'things' (sensor and actuators) always. There are huge number of scenarios like indoor network, underwater network, unfavourable weather condition when GPS do not work. So alternative techniques required. Hence development of huge number of techniques and protocol is done for these scenarios and localization plays an important role for services in IoT infrastructure. A major part of IoT infrastructure consists of heterogenous sensors so it can be called as sensing service on demand based on user. IoT infrastructure is a paradigm shift from traditional sensor network as shown in Fig. 2. It consists of a cloud or virtual sink which schedule and control physical sensor network based on location of users. Traditional WSN have grown into Sensor-Cloud architecture in IoT infrastructure. Here efficient sensor network are used for Sensing as a Service (SeaaS) model of the IoT infrastructure. The architecture of location based interactive model of IoT infrastructure [38], [39] is presented in Fig 2. The architecture consists of four layers.

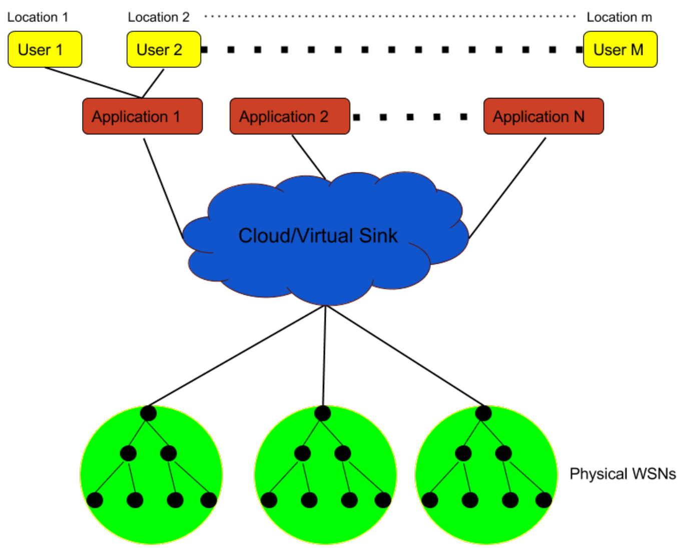


Fig. 2. Location based interactive model of IoT (showing IoT-Cloud-WSN integration)

- 1.Physical WSN Layer: This layer consists of physical sensor network. The characteristics of these sensors have sensor ID, state, location and ownership.
- 2.Cloud or Virtual Sink: The sensor layer forward their sensed data to cloud or virtual sink. The characteristics of cloud is cloud ID, QoS, resource and price. Cloud provides sensing service from different sensor network from different WSN with different owner. The cloud provide on demand sensing service Sensing as a Service (SeaaS).
- 3.Application Layer: Application layer provide different applications to the user and access services from cloud. The characteristics of application layer is application ID, region of interest, sensor data of interest and Quality of Services (QoS) requirements like sensing intervals, delays etc.
- 4.User Layer: User layer consists of user which use services through application. The characteristics of users are user ID, location, application ID etc. A single user can use multiple applications.

In the given LoT model of IoT infrastructure location information of 'things' are very important for providing services and application. The cloud should know the location information of user and sensors to provide services. To control and coordinate the 'things' (sensor and actuators) of IoT the virtual sink or cloud require location information a priori. Hence there is requirement of localization and prediction of 'things' (sensor and actuators) in IoT infrastructure. To schedule sensor for respective user location of user is important to the cloud or virtual sink. The advantages of this paradigm shift over traditional WSN are

- Energy efficiency of services due to optimization of sensors and services.
- This infrastructure provides on demand services based on quality of information.

Hence localization plays a key role in Sensor-cloud based IoT infrastructure.

III. Methodologies

In the last few years research is going on for finding the efficient algorithm for localization. The localization of sensor node is a two step process of first physical measurement with some reference and second estimate the location from the physical measurement data. Sometimes nodes with limited hardware do not conduct physical measurement rather they try to calculate the position from neighbour node information. The following approach for localization are existing in the literature. These are based on range measurement, available of anchor nodes, fine-grained, coarse-grained, incremental and concurrent localization method. The basis of classification of the above scheme are based on either anchor node or range measurement.

From the existing literature and IoT application it is found that there is a need of review of existing technology to address the localization problem to the IoT infrastructure. The selection of proper localization method in the IoT scenario aims to address the restriction and avoid the pitfalls. The proposed taxonomy classifies the localization approach based on offline training. Since IoT infrastructure analyses huge data and devices. There is huge scope of application offline training for localization. So training step is the key for taxonomical hierarchy of localization method in IoT infrastructure. The classification is presented in Fig 3. The localization approach are reviewed into two category considering IoT scenario as (1) Self Determining Method (2) Training Dependent Method.

A. Self Determining Method

Self determining method can be sub divided into four categories namely (1) Geometric Method. (2) Mobility model (3) Path planning (4) Statistical Approximation. The geometric method consider various geometric parameters to estimate location. This method check triangular information like lateration, angulation or connectivity among sensor nodes. This

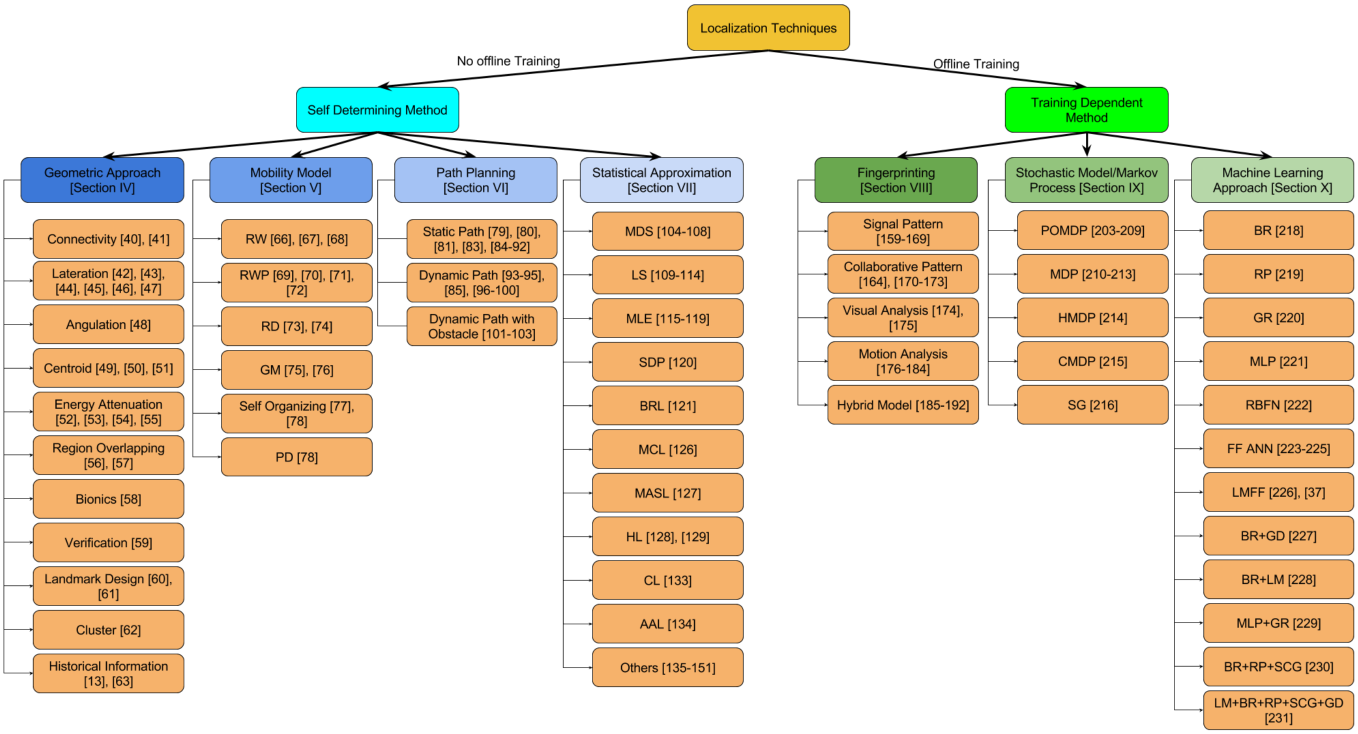


Fig. 3. Taxonomy of Localization Methods

method is categorised based on connectivity, centroid calculation, landmark design, region overlap, clustering etc. Mobility model take advantages the mobility pattern of anchor nodes of the network . The mobility pattern can be random or specified. This is further classified on the basis of mobility patterns like random walk, random direction, self-organisation etc. as shown in Fig. 3. Path planning is advanced version of anchor mobility model in which anchor node move in a specified path in the network to localize the whole network. Few scenario of this categories like static path model and dynamic path model have huge application in robotic sensor and actuator network. Statistical approximation techniques uses standard approximation methods like Least Square, Maximum Likelihood, Multi-Dimensional Scaling, Semidefinite Programming etc. to estimate location.

B. *Training Dependent Method*

These method uses an offline training phase before online localization step. These are classified into (1) Fingerprinting (2) Stochastic Model (3) Machine Learning approach. Fingerprinting method is further classified into signal, visual, motion and hybrid types of fingerprints. Stochastic Models can be of POMDP (Partially Observable Markov decision process), MDP (Markov decision process), SG (Stochastic Game), HMDP (Hierarchical Markov decision process) and CMDP (Constrained Markov decision process). Machine learning based approach is classified into LMFF (Levenberg-Marquardt Feed-Forward), RBFN (Radial Basis Function Network), BRGD (Bayesian Regularization Gradient Descent), RPML (Resilient Back-propagation Multilayer) and MLP (Multi-Layer Perceptron).

IV. Geometric Approach of Localization

This approach of localization exploit geometric info to find location. These methods are categorised as follows.

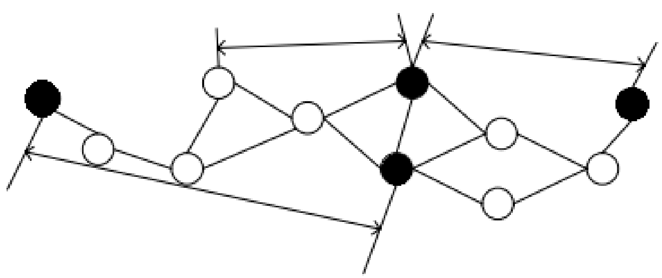
A. *Connectivity*

The range-free algorithm determines the pairwise distance of two nodes from the connectivity information. There are different types of classification such as connectivity [40] [41], centroid [49] [50] [51], energy attenuation [52] [53] [54] and Region overlap [55] [56] [57] and others [58] [59] [60] [61] as shown in the Table III. Connectivity method consolidates Graph theory with node's localization. Graphs with all the points joined are called connected graph. Network topology plays a significant role in connectivity based algorithms. There are two algorithms DV-Hop [40] and Localizable Collaborative Body (LCB) [41] which uses connectivity information. Initially the anchor node broadcasts its coordinate and hop count in vector packet.The node who receives the vector packet again broadcast it with increased hop count. In this way all nodes have a list of anchor node coordinate and the distance in hop count. Unknown node calculate the distance with the anchor nodes and find its position as shown in Fig. 4 (a). For efficient calculation, there is the requirement of at least three anchors in the range of unknown nodes. The density of anchor decreases the localization error.

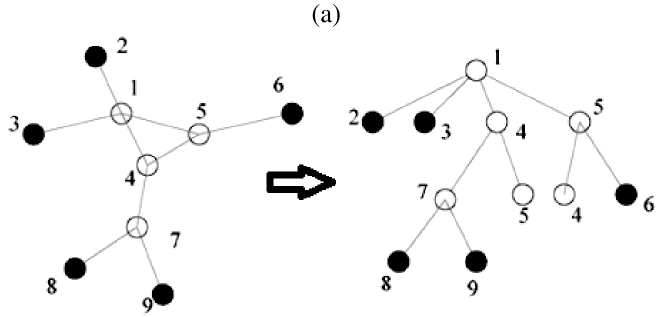
LCB also uses graph theory to localize unknown nodes with multihop anchors. LCB overcome the restriction of three anchors for calculating the position of unknown nodes with multihop anchors. In LCB all the anchors first announce their location information. The remote node acquires the location

TABLE III
GEOMETRIC APPROACHES OF LOCALIZATION

Localization Method	Algorithm	Sensor Density	Anchor Density	Accuracy	Power Consumption	Remarks
Connectivity	DV-Hop [40]	High	3 or more	High	High	High Energy Consumption but computationally simple
	LCB [41]	High	3 or more	High	Medium	Medium Energy Consumption computationally complex
Trilateration	DV-ARND [42]	High	3 or more	High	Medium	Cooperative method uses connectivity range measurement
	ECHO [43]	Medium	3 or more	High	Medium	Cooperative method
	DS Theory [44]	Medium	4 or more	High	Medium	Non cooperative method uses joint RSS and AoA range measurement
	RODL [45]	Medium	3 or more	Medium	High	Cooperative method uses TDoA range measurement
Multilateration	M-Mobility [46]	Medium	3 or more	Medium	High	Cooprative method relies connectivy information
	AFL [47]	Medium	3 or more	Medium	Medium	Acoustic sensors uses connectivity information cooperatively
Triangulation	ABC [48]	High	3 or more	High	Medium	Uses RSSI information cooperatively for estimation
Centroid	Centroid [49]	Low	3 or more	Low	High	High Energy Consumption but computationally simple
	ABC [50]	Low	3 or more	Medium	Medium	Medium Energy Consumption with complex computation
	Threedimensional Centroid [51]	Low	4 or more	High	High	High Energy Consumption and simple algorithm
Energy Attenuation	Source Energy Attenuation [52]	Average	3 or more	Medium	Medium	Medium Energy Consumption computationally simple
	BSR [53]	Average	3or more	High	High	High Energy Consumption and computationally simple
	Energy Interval [54]	Average	3or more	High	High	High Energy Consumption and computationally simple
	HiRLoc [55]	Small	3or more	Medium	Medium	Medium Energy Consumption with moderate complex
Region Overlap	APIS [56]	Low	3or more	High	Low	Low Energy Consumption and complex
	Voronoi [57]	Low	3or more	Medium	Medium	Medium Energy Consumption and moderate computation
Bionics	Honeybee Orientation [58]	Medium	3or more	Medium	High	High Energy Consumption and computationally simple
Verification	Weighted Centroid Algorithm [59]	Medium	3or more	Medium	Medium	Medium Energy Consumption and computationally simple
Landmark Design	RNST [60]	Low	3or more	High	Low	Low Energy Consumption and computationally simple
	Landmark Sparse [61]	Low	3or more	Medium	High	High Energy Consumption and computationally simple
Cluster	Target Tracking Algorithm [62]	No effect	3or more	High	High	Low Energy Consumption and complex
Historical Information	Distributed mobile Localization [37]	No effect	2	High	Medium	Medium Energy Consumption and moderate computation
	DTN [63]	No effect	3 or more	High	High	Medium Energy Consumption and moderate computation



(a)



(b)

Fig. 4. Connectivity approach of localization (a)DV hop Localization algorithm. (b)LCB algorithm evolves from BN tree with dark dots are landmark and hollow dots are unknown nodes.

information and modify the topology of the network and build a BN-tree. Unknown node estimate their position by the coordinates of the anchor nodes and modify the BN-tree as shown in Fig. 4 (b). LCB method reduces computing and communication cost, but it causes commutative localization error due to cooperative localization between unknown nodes.

B. Lateration/Trilateration/Multilateration

Wang et. al. [42] improved the DV-hop algorithm which uses regulated neighbourhood distance (RND) based on disk communication model of localization. RND method corrects the ambiguity in hop distance with the help of neighbouring node's proximity information. It is an adaptive method called DV-ARND. An iterative method for localization is proposed [43] in which a node's position is represented in barycentric coordinate system. It is an extension of Distributed Iterative LOCalization (DILOC) method [64]. This method solves the problem considering the pseudo linear system. Dempster-Shafer (DS) theory [44] is a novel method based on data fusion and Bayesian probability theory. A new method called Standby [65] is adopted with RSS and AoA which is used in DS Theory called as basic probability assignment (BPA) [65]. BPA considers best and worst case scenario with the lower bound, upper bound and confidence. This method first measures RSS, AoA, and standby distance. Then the filtering of the data is done and minimum and maximum values are taken for lower and upper bound of BPA. The BPAs are then aggregated,

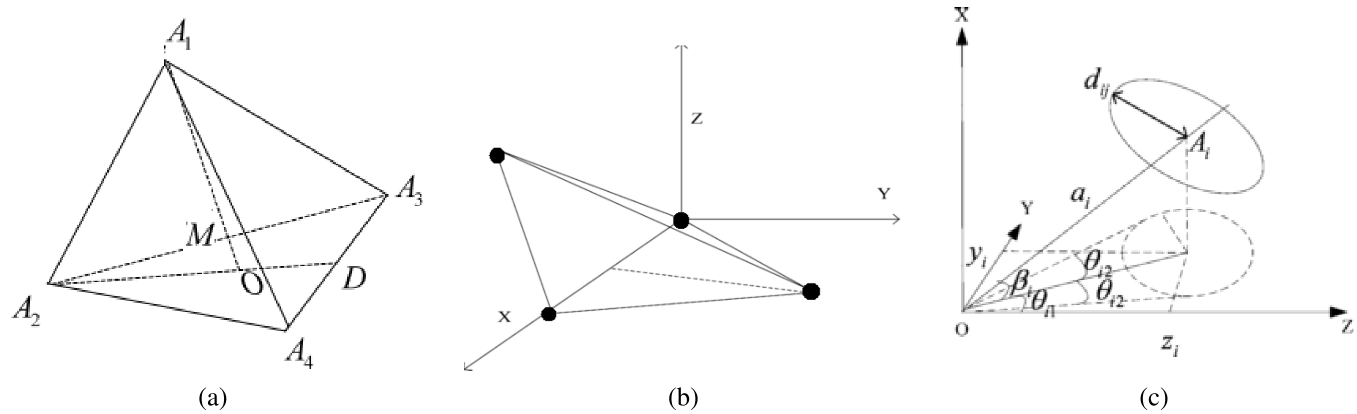


Fig. 5. Geometric Centroid Method (a)Tetrahedron method (b)ABC Method (c)Three dimensional Centroid algorithm

and most possible distance is predicted with lower and upper bound. Moore et. al. [45] proposed a Robust Distributed Network Localization (RODL). It is an anchor-free localization algorithm and considers noisy range measurement and flip ambiguity. First it forms cluster in the form of quadrilateral. After each cluster is localized, overlapping quadrilateral are found using numerical optimization. Finally, local clusters are combined using common nodes.

C. Angulation/Triangulation

Assumption Based Coordinate (ABC) [48] method uses range measurement to find a local position of each node. In this method, a node collects information about range measurement from all the neighboring nodes and localize itself. Each local position information is shared with the neighbors and forms a global map.

D. Centroid

Centroid approach uses connectivity knowledge for location estimation of the nodes. The anchor nodes periodically broadcast their location. For the calculation of location information unknown node find the centroid of the received locations of the anchor nodes. In [49] the author explained the centroid method in which the unknown node estimates the coordinate of the centroid of the tetrahedron as shown in Fig. 5 (a). There is two process of calculating the centroid one is a traditional method and other is to find the centroid of the tetrahedron. The localization error of tetrahedron method is $0.54R$, whereas traditional methods give error $0.7R$. So the tetrahedron centroid method improves 29% over traditional method. Since the calculation runs in many rounds for unknown nodes, so it causes high energy consumption. In [50] the algorithm incorporate DV-hop with Assumption-Based Coordinates (ABC) for localization. This is the augmented form of the DV-hop method in which first unknown nodes calculate distance information from the connectivity information using the DV-hop method and then apply ABC algorithm to find position information as shown in Fig. 5 (b). This is the simple computation with high error. Another novel method is three-dimensional centroid algorithm [51] which considers the unknown nodes in 3-D WSN. The method considers a geometric relationship with communication constraints to find the position. First three-dimensional graph is constructed taking into the anchor profile then it is converted to plane graph, and finally, a centroid of the plane graph gives the estimated position. In this method the localization accuracy is 99% with minimum 6 anchor nodes.

E. Energy Attenuation

Energy attenuation method uses signal energy pattern of the anchors to find the position of unknown nodes as shown in Fig.6 (a). The distance of the unknown node from the anchor is extracted from the attenuated signal energy. Sound energy is used to study this method. In source energy attenuation method [52], first the objective function is constructed with the help of maximum likelihood method then the position of the unknown node is estimated with the Gauss-Newton Method. By increasing the SNR (Signal to Noise Ratio), the positioning accuracy can be increased immensely. The biggest problem in this method is the impact of noise in signal propagation which involves error in the localization process. Beacon Signal Ring (BSR) [53] approach is a novel method in which the anchors broadcast signals of multiple power level to remote nodes. Each remote node receives and monitor power report and estimates the signal range based on the acquired information. This method has higher accuracy than the previous method but to transmit in different power the requirement of energy is more. Energy Interval [54] method estimate the coordinate of the unknown nodes based on Log-normal distribution representation of energy attenuation. Here a region mapping is done between the received signal power and the transmission range. From the received energy the unknown node estimates its transmission range. Then the region information is transformed to distance information of the overlapping region. The centroid of this overlapping region provides the position of the unknown node. The calculation is done with many rounds may rise the energy consumption.

F. Region Overlapping

Region Overlap method estimates the position of the unknown node by calculating the centroid of the overlapping

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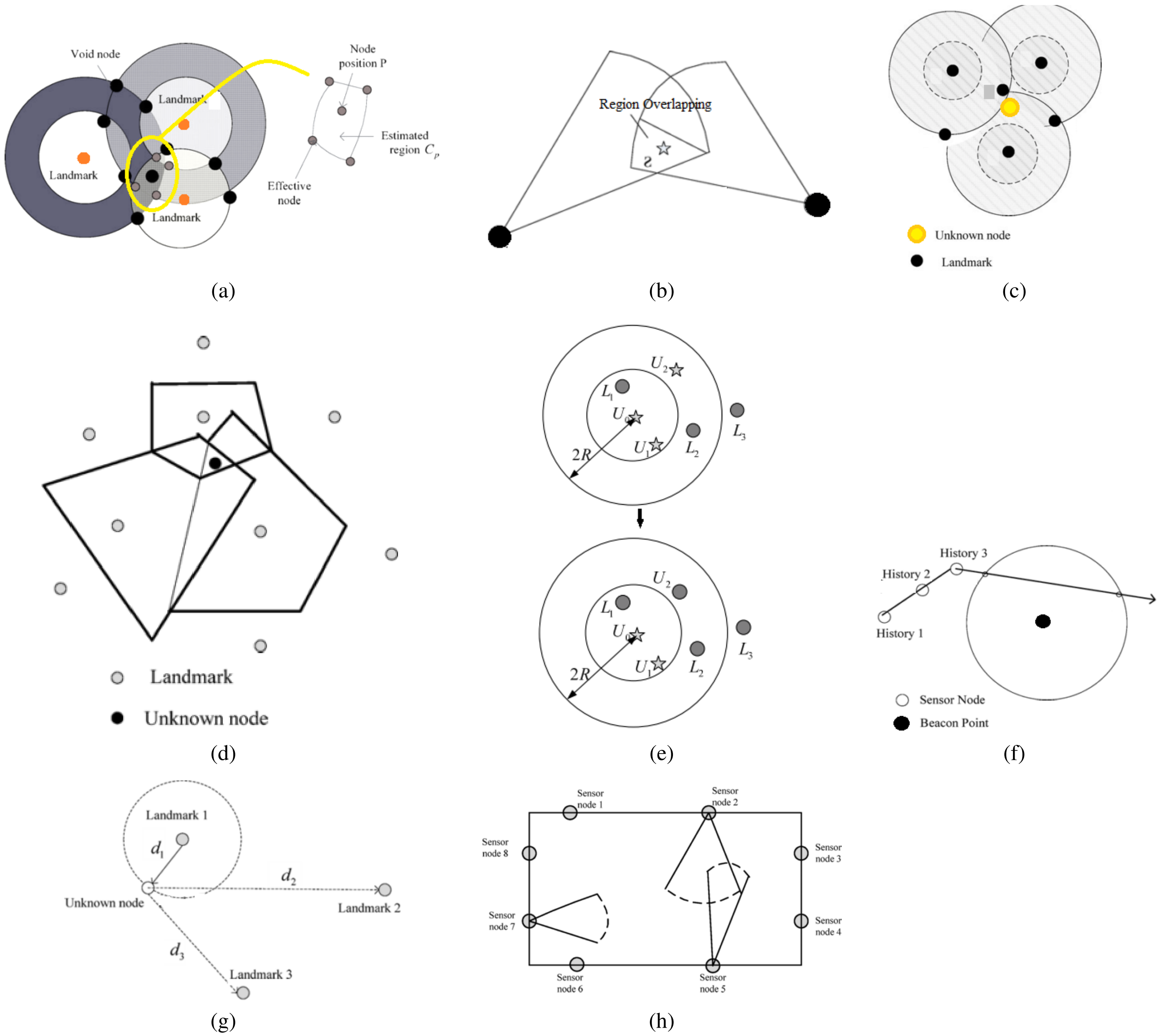

Fig. 6. Geometric Approaches (a)Energy grade overlap for energy attenuation method (b)Region Overlapping (c)Spherical shells overlap (d)Voronoi Graph (e)Left initial position and U2 updated landmark diagram. (f)Distributed mobile localization algorithm. (g)DTN Localization algorithm. (h)Target tracking algorithm.

region as shown in Fig. 6 (b). This method does not calculate the distance information. Hence, it reduces the communication cost and saves the energy consumption. There are three algorithms in this approach HiRLoc [55], APIS [56], Voronoi [57]. The HiRLoc [55] algorithm uses variable transmission power and variable angle of the directional antenna to reduce the overlapping region of the unknown nodes. The effect of anchor node become very less in this method. However, the communication cost is more as compared to other methods due to transmission and the directional antenna. To reduce the communication cost a similar method called Spherical shell overlap method APIS is proposed in [56]. In this method anchor node broadcasts location information in the spherical form and the unknown node receives and calculates the position. Number of the data packet in HirLoc is less compared to APIS [56] method. Voronoi graph [57] method is another promising method in which the unknown node sort the RSSI (Received Signal Strength Indicator) in descending order of the anchor and calculate the Voronoi region of the anchor using Unit Disk Graph followed by finding the centroid of the Voronoi overlap region. This centroid is the position of the unknown node. Here the Localization error increases as the communication space and anchor density decreases.

G. Bionics

Bionics algorithms consider the biological motion and try to mimic it to localize sensor nodes. The algorithm establishes a relationship between the position of the unknown node and

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the anchor based on the laws of biological motion. The habits of the bee in the physical world for searching nectar is used for the localization of unknown node [58]. This algorithm first computes the distance from nearby anchor according to signal strength then using the cosine law estimate the relative angle and obtain the relative position based on the bees model. Here accuracy is high and hardware cost is also high.

H. Verification

Verification localization method estimates pairwise distance from the RSSI information. First, the algorithm estimates the pairwise distance of the nodes from RSSI information then verify the weight value using distance and RSSI and further estimates the position. In this method, localization error is less as compared to weighted centroid algorithm [59].

I. Landmark Design

Landmark placement has a significant effect on localization error. These placement methods use the different geometry of positioning of the anchors which reduces the localization error of unknown nodes. Reference Node Selection based Triangulation (RNST) [60] shows less error in localization if the anchors construct an equilateral triangle. Landmark Upgrade method is another method to increase the accuracy of localization. In WSN the number of the anchor is limited so all the unknown nodes do not get three neighboring anchors. This problem is solved with updating accurate estimated non-achor unknown nodes to anchor nodes. This method causes more communication cost but increases accuracy [61].

J. Cluster

Cluster-Based Algorithm have lower computational complexity. These algorithm first divides the region into the clusters. Each cluster is associated with one anchor node. Each anchor localize unknown nodes of the cluster and finally, all the localized information is merged, and final estimation is done. The distributed target tracking algorithm [62] is a cluster based algorithm which first divides the region into the cluster with one anchor node. The anchor node takes care of establishing the connectivity assigning the task and target tracking. When the unknown node moves into the different group, the respective anchor node of the cluster cooperatively estimate the position.

K. Historical Information

The concept behind the historical information method is to take the historical information to estimate the current position. Here first maintain a queue of at least three location of the unknown node and form the linear motion equation followed by the estimation of the location [37]. Dynamic Triangular Network (DTN) [63] Algorithm predict the location with the help of RSSI information of the unknown node. Here the algorithm first considers the possible location with respect to the anchor nodes and then estimates the distance from two anchor nodes. The error is calculated from estimated distance and actual distance and compared. The lowest distance from the anchor is considered as the position of the unknown node.

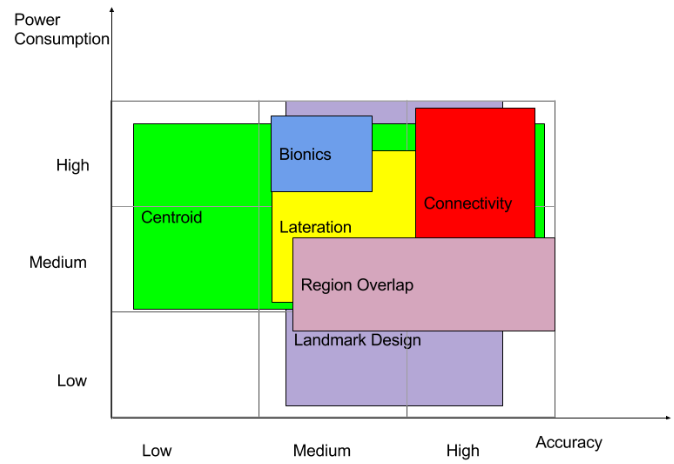

Fig. 7. Comparison of different geometric localization approach with respect to accuracy and power consumption

L. Summary and Insight

The existing geometrical method exploit the geometric architecture of the network to optimise accurately and power consumption. The reviewed article compared on the basis of accuracy and power consumption and a comparative chart is plotted and analysed. Landmark design and region overlap method gives promising result than other method in terms of accuracy and power consumption as shown in Fig. 7.

V. Mobility Model

The different mobility pattern of anchor nodes are exploited in this method to find the geographical location. These are explained as follows.

A. Random Walk Model

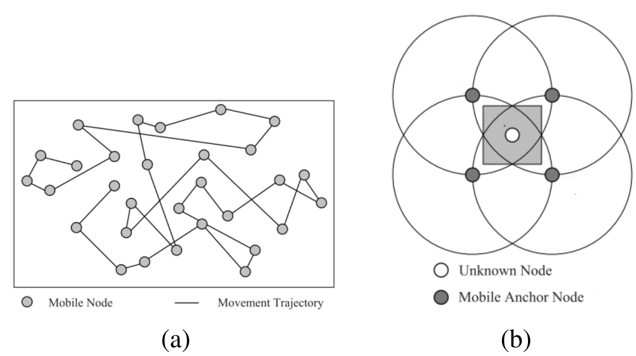

Fig. 8. (a) Random Walk Mobility Mode. (b) Possible area in DOL algorithm

Random Walk Mobility Model [66] [67] [68] is used by the anchor node to move in the network from one point to another point with a random velocity and random direction. Here current speed and direction are independent of the past speed and direction.

Moving Aerial Robotic Beacon (MARB) [66] localization is based upon the RSSI measurement technique. There is a relation between distance and RSSI value of the unknown nodes to the anchor nodes. A Bayesian framework is used

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TABLE IV
MOBILITY MODEL APPROACH OF LOCALIZATION

Localization Method	Algorithm	No. of Anchors	Anchor Utilization	Accuracy	Power Consumption	Remarks
RW	MARB [66]	Single	Low	High	Medium	Not Complete Localizable due to Random Walk
	MBL-MDS [67]	Single	Low	High	Medium	Sufficient Reference Required
	DOL [68]	Single	Low	Medium	Low	Simple technology used
RWP	Ssu [69]	Single	Low	Medium	Low	No Extra Hardware since Range-free
	RAA [70]	Single	Low	Medium	Low	No Extra Hardware since Range-free
	Yu [71]	Single	Low	Medium	Medium	Mobile Trajectory is straight
	LMCS [72]	Single	Low	High	High	More Energy Consumption but Better Performance in Obstacle Environment
RD	Finegrained [73]	Single	Low	High	Low	Better than Ssu [67]and Yu [69] but more cumulative localization error
	ADO [74]	Single	Low	Depends RSS model	Medium	Choice of RSS model is important
GM	FAL [75]	Five	High	Medium	Low	Simple technology used
	NAL [76]	Nine	High	High	Low	Less energy consumption due to no distance estimation
Self Organising	Time-based [77]	More	High	Average	High	High travelling speed with High energy consumption
PD	MCL [78]	More	Low	High	High	Medium travelling speed with High energy consumption

to estimate the location of the unknown nodes where the conditional probability is the measure of the position. Here the position is estimated and updated recursively. Mobile Beacon

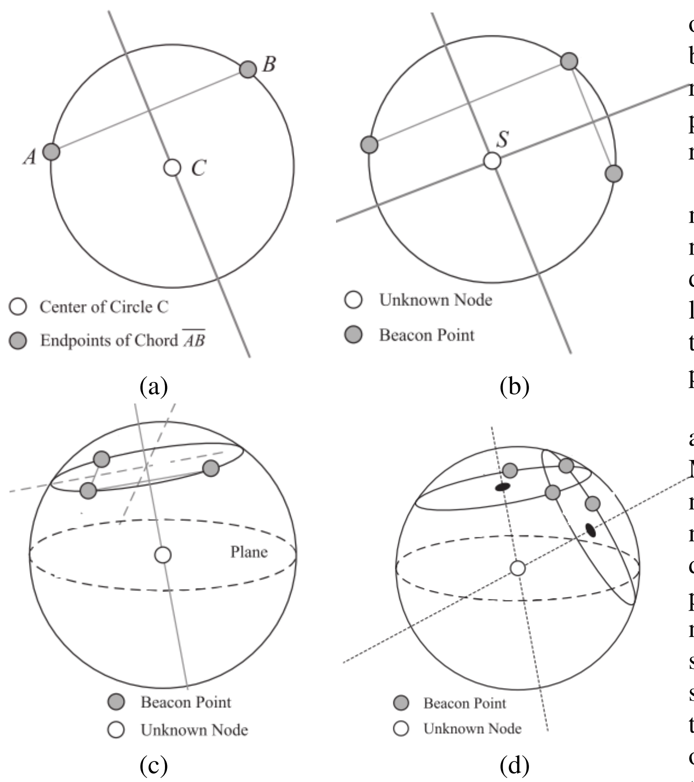

Fig. 9. Random Way Point (a)Perpendicular bisector of Chord (b)Localization With Mobile (c)Localization with aerial (d)Localization with flying anchors

Localization (MBL) [67] uses the classical Multidimensional Scaling (MDS) with connectivity information in mobile anchor nodes. Here the mobile anchor broadcasts the beacon packets in each point and the unknown node receives and estimates the position using MDS. It is applicable in 3D Network.

In Distributed Online Localization (DOL) [68] first, the mobile anchor nodes broadcast the beacon packets. In the reception of beacon packets, the unknown node approximates its position using rectangular bounding box. Further, it finds the centroid of the estimated location of the several beacon packets which reduces the complexity, but the error is quite more.

B. Random Waypoint Model

K. F. Ssu et. al. [69] demonstrated a range free method of localization of mobile anchor nodes using perpendicular bisector of the chord in which the endpoint of the chord represents the two anchor nodes. These two sets of the perpendicular bisector of the chord intersect at a point, which represents the localization of the unknown node.

Range-free Aerial Anchor node (RAA) [70] localization method is proposed for the network with the mobile anchor node. In RAA method a circular cross section is formed by the different beacon position of the anchor node.A perpendicular line is drawn from the centre point of the circular cross section to the unknown node plane. This point is estimated as the position of the unknown node.

Yu et. al. [71] modified the previous algorithms [70] [69] and proposed an algorithm with a flying mobile anchor nodes. Many circular cross section can be drawn by different anchor nodes. The perpendicular lines are drawn from the unknown node to the centre point of the circular cross section of different mobile anchors. The intersection point of different perpendicular lines is estimated as the position of unknown node. Localization with a Mobile Beacon based on Compressive Sensing (LMCS) [72] is a mobile anchor based range free scheme. LMCS uses comprehensive sensing (CS) to prepare the related order of the unlocalized nodes. From the related order, LMCS selects the weight of each point and computes the location of the unknown node by weighted centroid.

C. Random Direction Model

Random Direction (RD) movement model [73] [74] assumes that anchor move in a random path till the boundary of the deployed network region as shown in Fig.10 (a). After a pause anchor node again take a new direction randomly from zero to 180 degree to move.

The fine-grained method [73] is also a range free method. It is a updated method described by K. F. Ssu et. al. [69] and C. Zhao et. al. [71]. In this method possible positions can be calculated using the analytical method. The position of the unknown node can be finalized from the possible positions using the mobile anchor node.

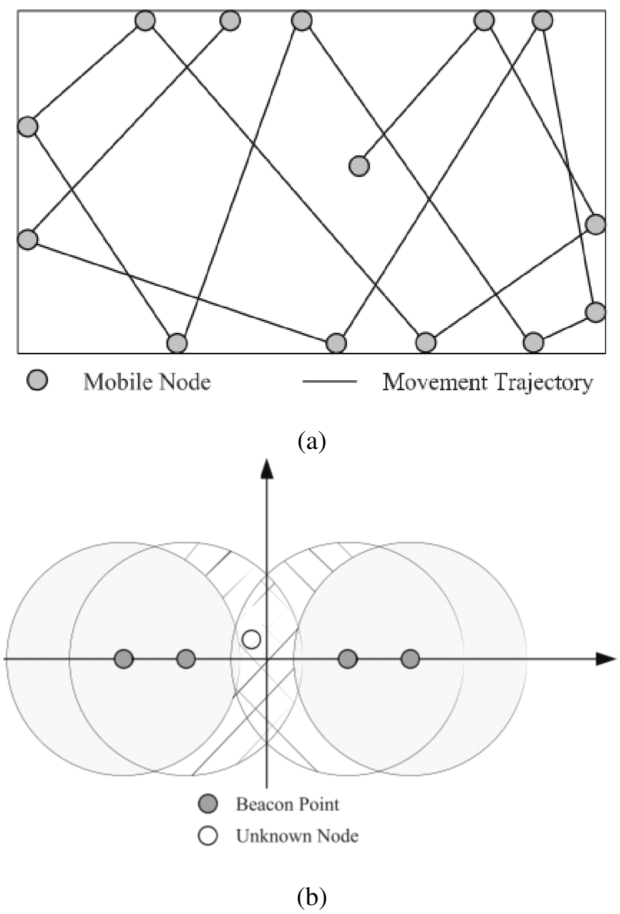

Fig. 10. Random direction Mobility Model (a)Model showing the path (b)Localization using arrival and leaving information of the beacon

Arrival and Departure Overlap (ADO) [74] is a distributed localization method. ADO uses different mobility models sparse straight line, dense straight line and random movement pattern. The location of the unknown node is estimated as the intersection point of received beacon signals from the mobile anchor nodes as shown in Fig. 10 (b).

D. Group Mobility Model

Group mobility model consist mobility of more than one anchors at a time as shown in Fig. 11. This method compares the movement of the transmitted RSS and geometrical information. Here unknown nodes can estimate their position without much interaction. The primary two methods are Five Anchor Localization (FAL) [75] method in which four anchors located in a square with one unknown node at centre based on RSSI. Another method is the Nine Anchor Localization (NAL) [76] which uses eight anchors in a circle with one unknown node at the centre using the RSSI. Multiple anchor localization uses a particular geometric pattern and mobility model of the anchor node in the network.

E. Self Organizing Model

Time-based algorithms rely on the continuous movement of the anchor nodes to localize unknown nodes. The main concept of this algorithm is to determine the position of the remote nodes for a short period. A self-organization method [77] consider unknown nodes static for a certain interval and send beacon packet in this interval to localize. When unknown node get enough beacon to calculate the position, it uses the trilateration method to calculate its position.

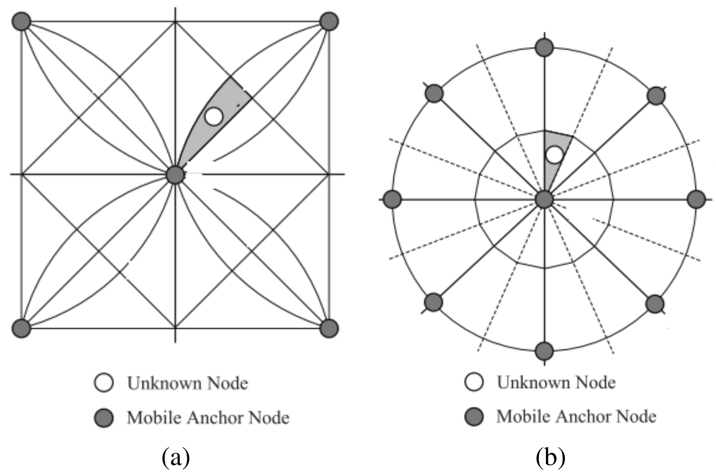

Fig. 11. Group Mobility Model:(a)Possible Area in FAL(b)Possible area in NAL

F. Probability Distribution Model

Probability distribution method uses prior probability to estimate the location of the unknown nodes. Dynamic Monte Carlo Localization (MCL) [78] method has two stages of localization; prediction and filtration. In prediction stage, the node forecasts its position based upon preceding probability distribution of the network reserved. In filtration stage, the node discards the incompatible position information from the network. The main disadvantage is that it require a reserved information. The complexity of this method is very high.

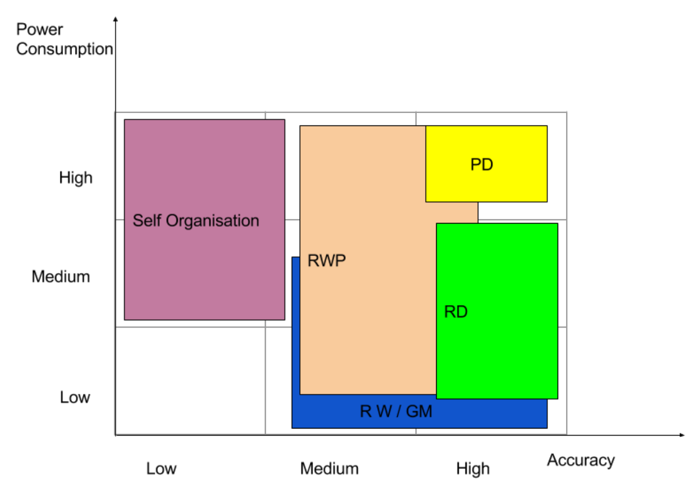

Fig. 12. Comparison of different Mobility-Based localization system with respect to accuracy and energy efficiency

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TABLE V
PATH PLANNING APPROACH OF LOCALIZATION

Localization Method	Algorithm	Area Coverage	Number of Mobile Anchors	Localization Accuracy	Power Consumption	Anchor Utilization	Remarks
Static Path	Lines [79]	No	Sngle	90%	Low	Low	Simple path planning but needs extra hardware for long communication range.
	SCANS, DOUBLE-SCAN, HILBERT [80]	No	Single	90%	Medium	Low	Many collinear anchors wasted.
	CIRCLES [81]	No	Single	70%	Medium	Low	Non-collinear anchors with Shorter path lenght than [82]
	MACL [83]	No	Single	50%	Medium	Low	Non-collinear anchors with shorter path length.
	GMAN [84]	Yes	Multiple	90%	Medium	Low	Synchronisation in movement of anchor.
	K-Coverage [85]	Yes	Single	70%	High	Low	Ensure k-coverage but long trajectory length.
	PI [86]	Yes	Single	90%	Medium	Low	Energy consumption for turns not considered
	LMAT [87]	Yes	Single	70%	Medium	Low	Energy consumption for turns not considered
	S-Type [88]	Yes	Single	90%	High	Low	Much energy consumed for turn but solved collinearity problem.
	SCAN Based [89]	Yes	Single	95%	High	Loow	Longer path length but fully localisable network.
	WCL [90]	No	Multiple	90%	High	Low	Beacon collinear problem present
	Layered Scan [91]	No	Single	90%	High	Low	Applicable for 3D localisation more path length more energy consumption
	HL [92]	Yes	Single	80%	High	Low	Applicable for 3D localisation more path length more energy consumption
Dynamic Path	MBAL [93]	No	Single	50%	Medium	High	Works well in ununiform WSNs but not consider obstacle environment
	BRF and BTG [94]	No	Single	95%	Medium	High	High anchor utilisation
	MBL (nde) [95]	No	Single	90%	High	High	Dynamic algorithm but Highest complexity
	Virtual Force [85]	No	Single	90%	Medium	High	Works well in ununiform WSNs but needs directional antennae
	MALS [96]	No	Single	90%	Medium	High	Applicable for Large scale WSNs but high localisation delay.
	SPNP [97]	No	Single	50%	Low	High	Less computational load but high localisation delay.
	DREAMS [98]	No	Single	90%	Medium	High	Node failure is a major problem.
	Anchor Guiding [99]	No	Single	90%	High	High	Can balance the localisation error but computational complexity is high.
	3DVFDPP [100]	No	Single	90%	High	High	Avoid movement in no sensor field but calculate virtual force in all directions leads complexity.
Dynamic Path+Obstacle	Virtual Ruler [101]	No	Multiple	80%	High	High	applicable to obstructed WSNs with ultrasound transmitter
	Snake Like [102]	No	Single	90%	Medium	High	Use minimum beacons but applicable only for known obstacles.
	Visibilty-Binary Tree [103]	No	Single	90%	Medium	High	Shortest travelling path but long localisation delay.

G. Summary and Insight

Mobility model concentrates the movement pattern of the anchor nodes. The more the coverage of the mobile anchors more the sensor can be localized in a network. The six categories of methods like random walk, random direction, self organizationn, Random waypoint, Group Mobility and Probability Distribution are reviewed. It is found that some method requires sufficient reference when other uses simple hardware with RSSI. A comparative analysis chart is drawn of those method and shown in Fig. 12. RW and RD methods found to be outperform other methods in terms of accuracy and energy consumption.

VI. PATH PLANNING APPROACH

Path Planning tries to improvise the localization accuracy with a best possible trajectory of the mobile anchor node. Problem of path planning is to design a trajectory which

- Passes maximum nodes in the network.
- Provides each node with sufficient number of anchors.
- Reduces the energy consumption using the shortest trajectory length.

The path planning method can be of two types; first is static in which the path is predefined and second is dynamic in which path can be changed.

Static Path Planning can be of two types such as two dimensional and three dimensional. In two-dimensional path planning anchor traverse in the two-dimensional plane [79]-[88].

In Lines [79] the anchor node moves in the X-axis of the region and broadcasts gradient signals to localize the unknown node. It is independent of unknown node density.

Based on the scan it can be SCAN, DOUBLE SCAN, and HILBERT [80]. It maximize the network coverage. The simple SCAN moves the anchor and scan in the x-axis. The DOUBLE SCAN moves the anchor in both direction but HILBERT SCAN moves the anchor node in the Hilbert pattern.

Circle and S-curve are two other methods [81]to reduce localization collinearity. This types of scan leave the corner of the region.

Mobile Anchor Centroid Localization (MACL) [83] is proposed, in which the anchor node traverse in a spiral path and periodically broadcast the beacon packet which contains the current location.

Group Mobile Anchor Node (GMAN) [84] contains three anchor nodes which construct an equilateral triangle with all anchor at the vertex. In two-tier network architecture, the anchor group move in the x-axis or in a random pattern.

K-coverage [85] is employed to diminish beacon density and trajectory range. This method contains two steps. In the first step, an optimal 3-coverage is used for deployment of virtual beacons. In the second step, the ant colony optimization is used to create a movement pattern for a mobile anchor to pass the virtual beacons. Perpendicular Intersection (PI) [86] method uses perpendicular intersection to determine node position. The mobile anchor node starts at one position and move zigzag manner with an angle $0 < \theta < \pi/3$

Localization with Mobile Anchor using Trilateration (LMAT) [87] presents the progress of mobile anchor nodes in triangular trajectory to improve the localization accuracy. The major advantage of this method is that it can estimate the position even if the beacon points are collinear.

S-type is another method [88] in which the mobile anchor node moves in an S-type movement in the network area. The network area is divided into the small square of size $R/\sqrt{2}$. This method can maintain the shortest path for the trajectory and collinearity problem is solved. SCAN Based method [89] is based on scan algorithm in which nodes can identify three or more anchors to form two nonparallel chord of a circle. The length of each chord is allowed to take a specified value to reduce the error. The anchor node will move taking a scan and when finding an obstacle it will bypass nearby obstacle crossing in the right-hand direction. After

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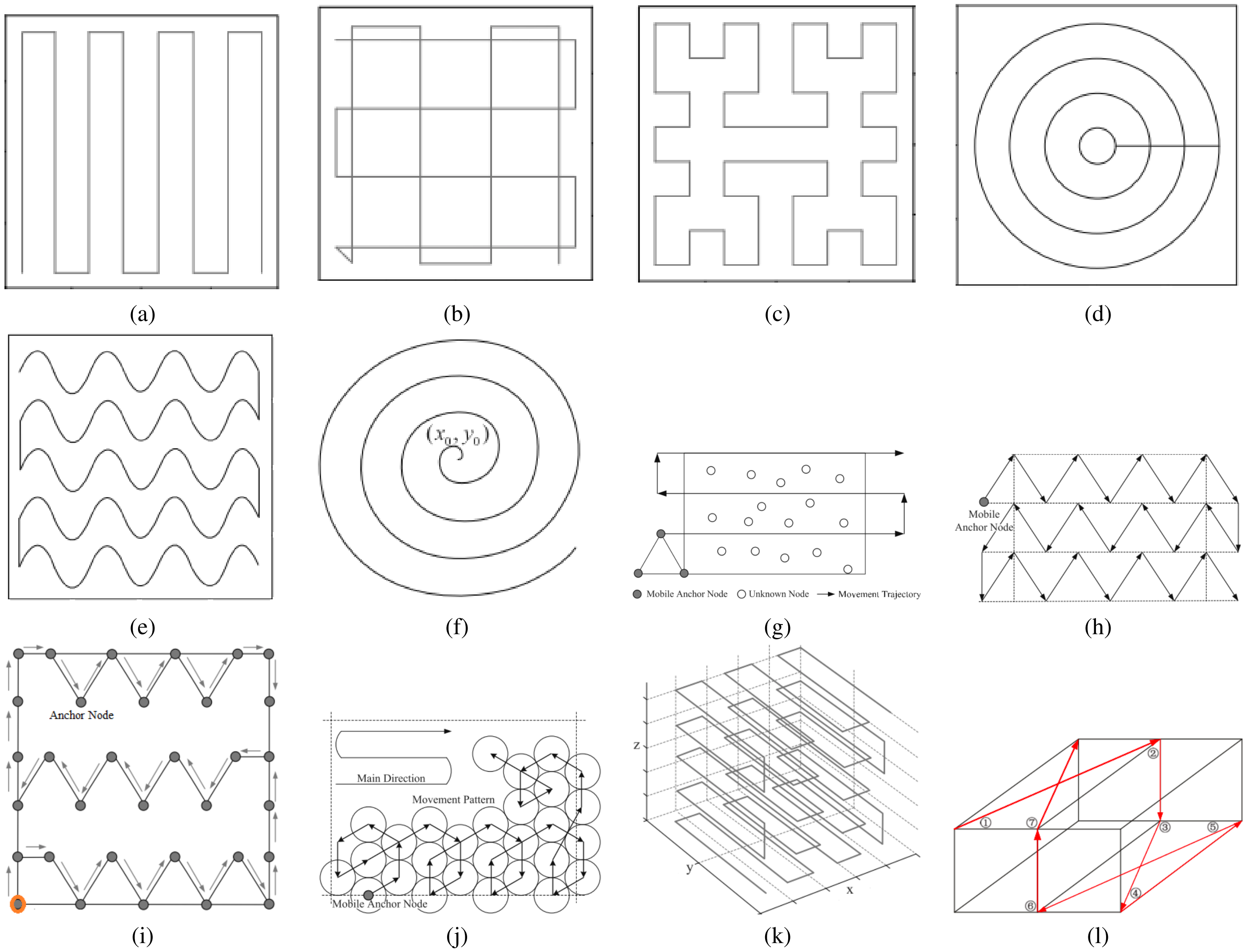

Fig. 13. Static Path Planning of anchor node for localization:a)SCAN (b) Double Scan (c) Hilbert (d) Circles (e) S-Curves (f) Trajectory of MACL (g) Trajectory of GMAN (h) Trajectory of PI(i) Trajectory of LMAT (j) Trajectory of S-type (k) 3D Scan (l) HL trajectory

bypassing, the anchor node returns to its previous path.

A Weighted Centroid Localization (WCL) [90] method has been proposed. In WCL four mobile anchor nodes forms the tetrahedron and moves as the layered scan trajectory. Hence it can cover the three dimensional area of the network.

The Layered Scan [91] is the modification of the 2D scan in 3D. Here the 3D region is divided into layers and each layer is scan using 2D scan methods and S-curve method to reduce collinearity and co-planarity.

Hexahedral Localization (HL) [92] is a 3D path planning based localization in which space is divided into hexahedrons. Unknown nodes can be localized using the perpendicular characteristic of the route. Mobile beacons move in the path and continuously broadcast their position information and the unknown nodes take the position information and calculate their position.

The use of single anchor node is more economical than multiple anchor nodes, but it gives issues like collinear and co-planner. Multiple anchors can solve these issues with better localization in the 3D sensor network but still they are unable to localize in the dynamic and real-time sensor network. So there is the requirement of active route plan. Since motionless route preparation considered the sensor nodes to be disposed uniformly. But in real scenario sensors are distributed non-uniformly so it is very hard to localize. Static path plan takes the long route, time delay and under utilization of beacon messages. So to improve these issues, there is a proposal of dynamic path planning. It is of two types one is without obstacle and second is with obstacle. So obstacle detection and avoidance are the requirements in the current research.

Mobile Beacon-Assisted Localization (MBAL) [93] is consists of three steps. First anchor movement step, Second sensor localization step and finally the path decision step. The mobile anchors move in a regular triangle and broadcast three beacon packets. When the remote nodes demand more beacon packet, then the anchor node determines the trajectory of the request, and move towards the demand to reduce the path length.

A method has been proposed [94] for Dynamic path planning. In this the network is considered as an undirected graph where vertices of the graph are unknown nodes. Breadth First

(BRF) and Back-Tracking Greedy (BTG) algorithm is used to form the path for the anchor node by traversing the undirected graph. The movement of the anchor node varies dynamically according to the path.

Mobile beacon-assisted localization (MBL) [95] considers the node distribution information of the network. It divides the network based on clusters. Mobile anchor first traverses all the group head using the genetic algorithm. Then the anchor moves in a regular hexagon in particular cluster including cluster head in the middle of the hexagon. Optimal movement is obtained from the local and global path. It improves localization accuracy and reduces the power consumption.

Dynamic anchor movement trajectory based on the potential field is a new idea [85]. An interaction between mobile anchor nodes and unknown nodes is created in this method. In non-uniformly placed network, sensor nodes are placed with omnidirectional antenna and anchor nodes with the directional antenna. Anchor node sends information in a fixed direction and receives feedback to calculate total virtual force. This total virtual force helps the anchor to decide which direction it has to move.

Accomodating non-uniform and irregular sensor network with the mobile anchor is proposed in Mobile Assisted localization by stitching (MALS) [96]. It takes the rigidity theory to partition the network with small localizable units. The final path for the anchor node is obtained by joining all the units.

Six Possible Next Position (SPNP) [97] method is proposed by Li et. al. This method utilize anchor routes to localize unknown nodes. First, three anchor nodes are placed randomly as they form an equilateral triangle. Then the next three anchor node are placed in the position where they can cover more number of unknown nodes. This method is computationally efficient and consume low power.

Deterministic Beacon Mobility Scheduling (DREAMS) [98] method presents a new idea in which each anchor (beacon) traverse a path in the network and produce a traversal tree. The traversal tree is used to find the path of the mobile anchor (beacon) by distance-based heuristic method.

An anchor guiding method [99] is proposed based on the size of the estimated region. The unknown node and anchor nodes have some estimated rectangle region.When the unknown node receive the beacon from the anchor a new region called broadcasting region is formed. Anchor node try to move in the broadcasted region and consider this as the estimated rectangle region. Three-dimensional virtual force dynamic path planning (3D VFDPP) [100] assumes that there sensor nodes make a team. Sensing zone of the mobile anchor node is partitioned into eight zones. The anchor grow according to the virtual force from a certain direction. It will have the tendency to move in that direction.

Since there is not always the cases in sensor network without the obstacle, so few algorithms are proposed for obstacle based path planning for anchor nodes.

A Snake Like [102] anchor movement algorithm is proposed in which anchor node moves as snake. When it hit some obstacle, it detours the path and saves the obstacle point for future movement.

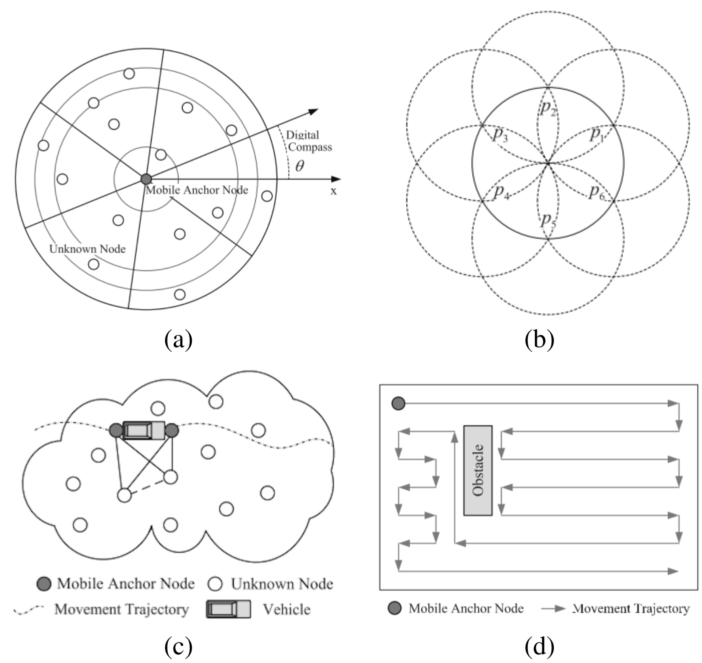

Fig. 14. Dynamic Path Planning of anchor node for localization:(a)MBAL (b) SPNP (c) Virtual Ruler (d) Snake Like Obstacle Avoidance

Visibility binary tree (VBT) [103] is an obstacle avoidance method. In VBT all of the tangent paths between obstacle is drawn. Then the redundant paths are reduced. Finally, it apply an ad-hoc searching algorithms to form an optimal binary tree to calculate the shortest path.

A. Summary and Insight

Another similar method to mobility pattern based approach is path planning approach gains huge interest in current localization techniques. Reviewing existing literature of path planning and considering static, dynamic and obstacle avoiding path planning of anchor nodes. It is found that the anchor node is very limited in these method. Few algorithms use extra hardware to maintain the anchor node movement. Majority of the algorithm used collinearity principle of anchor nodes. Anchor utilisation has a huge impact on accuracy and power consumption in these approaches.

VII. Estimation/Statistical Approximation Approach

The methods in this category uses various statistical approach to estimate the location information. This method is further classified into following.

A. Multidimensional Scaling (MDS)

Multidimensional Scaling (MDS) [104] is a range based distributed algorithm in which pairwise distance between the nodes is calculated to form a local map. It is further stitched to form the whole map to get the spatial coordinates. There are two types of MDS: Classical MDS and Iterative MDS. MDS-MAP [105] is a good solution for anchor free range-free localization problem. It consists of three steps. First,

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TABLE VI
ESTIMATION/STATISTICAL APPROXIMATION APPROACH

Method	Algorithm	Centralized/Distributed	Range Measurement	Architecture	Accuracy	Remark
MDS	Distributed MDS [104]	Distributed	RSSI	Cooperative	Medium	Immobile nodes with scalable
	MDS-MAP [105]	Centralized	Connectivity	Cooperative	Medium	Immobile nodes not scalable
	MDS-MAP (D) [106]	Distributed	Connectivity	Cooperative	Medium	Medium node density
	Map-Stitching [107]	Centralized	Connectivity	Cooperative	High	Work on dense network
	Patch and Stitch [108]	Centralized	Connectivity	Cooperative	Medium	Work on dense network and scalable
LS	LWUPLM (Localization with Unknown Path loss Model) [109]	Distributed	RSSI	Non Cooperative	Medium	Immobile scalable nodes
	EEL (Energy Efficient Localization) [110]	Distributed	RSSI	Non Cooperative	Medium	Immobile scalable nodes
	LLSE [111]	Distributed	RSSI/ToA	Non Cooperative	Medium	Immobile scalable nodes
	SOCP+SDP/SOCP [112]	Centralized	RSSI	Both	High	Immobile scalable nodes
	MSL [113]	Centralized	ToA	Non Cooperative	Medium	Immobile scalable nodes
	Distributed LS [114]	Distributed	Non Specified Range Measurement	Cooperative	Medium	Immobile scalable nodes
MLE	C-ML [115]	Distributed	RSSI	Non Cooperative	High	Work on static netowrk
	fGn [116]	Centralized	Acoustic	Non Cooperative	High	Mobile scalable nodes
	Distributed ECM [117]	Distributed	ToA	Cooperative	Medium	Mobile scalable nodes
	Mobility Aided SDP [118]	Distributed	ToA+RSSI	Non Cooperative	Medium	Mobile scalable nodes
	ADMM [119]	Distributed	Connectivity	Cooperative	Medium	Mobile scalable nodes
SDP	SLNN [120]	Centralized	ToA	Non Cooperative	High	Not scalable
ILS	BRL (Bayesian Ranging Method) [121]	Centralized	RSSI	Non Cooperative	Medium	Immobile scalable nodes
Spectral Regression	DESR [122]	Centralized	Connectivity	Cooperative	High	Immobile scalable nodes
IML	PL [123]	Both	ToA	Non Cooperative	Medium	Immobile scalable nodes
RA	HSL [124]	Distributed	RSSI+Connectivity	Non Cooperative	High	Immobile scalable nodes
FP	DWKNN [125]	Distributed	RSSI	Non Cooperative	High	Mobile and scalable nodes
MCL	Hit Ball [126]	Distributed	RSSI	Non Cooperative	Medium	Mobile and scalable nodes
MASL	MASL [127]	Centralized	ToA (One way ranging)	3D Mobile	High	No Anchors and Active Messaging
HL	HL [128] [129]	Centralized	TDoA	2D Stationary	High	Stationary Anchor with Active Messaging
ALS	ALS [130] [131]	Centralized	Range Free	2D Stationary	High	Anchors with variable power levers and active messaging
3D-MALS	3D-MALS [132]	Centralized	ToA(One-way Ranging)	3D Mobile	High	Mobile anchors (Electro-mechanical motion) with active messaging
CL	CL [133]	Centralized	ToA (One way ranging)	3D Mobile	High	No Anchors and Active Messaging
AAL	AAL [134]	Distributed	ToA (two-way Ranging)	3D Hybrid	Medium	Propelled mobile anchor (AUV) with silent messaging
LDB	LDB [135] [136]	Distributed	Range-free	3D Hybrid	Medium	Propelled mobile anchor (AUV) with silent messaging
DNRL	DNRL [137]	Distributed	ToA (One-way ranging)	3D Mobile	Medium	Non-propelled mobile anchors with silent messaging
MSL	MSL [138]	Distributed	ToA (One-way ranging)	3D Mobile	High	Non-propelled mobile anchors and reference nodes with active messaging
LSHL	LSHL [139]	Distributed	ToA (one-way Ranging)	3D Stationary	High	Surface buoys, underwater anchors and reference nodes with active messaging
DETL	DETL [140]	Distributed	ToA (One-way ranging)	3D Mobile	High	Surface buoys with DETs, underwater anchors and refreence nodes with active messaging
3DUL	3DUL [141]	Distributed	ToA (two-way ranging)	3D Hybrid	High	Three initial anchors and reference nodes with active messaging
AFL	AFL [142] [143]	Distributed	Not specified	3D Stationary	High	Anchor-free (One initial seed) with active messaging
UPS	UPS [144] [145]	Distributed	TDoA	3D stationary	Low	Four stationary anchors with silent messaging
WPS	WPS [146]	Distributed	TDoA	3D Stationary	Low	Four or five stationary anchor with silent messaging
LSLS	LSLS [147]	Distributed	TDoA	3D Stationary	High	Stationary Anchors with active messaging
USP	USP [148] [149] [150]	Distributed	Not specified	3D Stationary	High	Stationary Anchors with active messaging
SLMP	SLMP [151]	Distributed	ToA (One-way ranging)	3D Mobile	High	Surface buoys,Underwater anchor and refreence node with active messaging

the smallest route is calculated by connecting a couple of nodes and a pairwise distance matrix is formed. Then using this pairwise distance matrix 2D or 3D map is constructed which shows the position of all the nodes. Finally, the absolute position of all the nodes are estimated using the known nodes. This algorithm performs better than other algorithm, but performance goes down when more number of anchor nodes presented in the network.

MDS-MAP is further improved into distributed form called MDS-MAP (D) [106] using positioning local maps. First, this algorithm calculates local map using MDS-MAP then these local maps are connected based on adjacent node common among these local maps. The local maps are aligned further, and least square method is used to minimize the distance between the neighbor nodes.

A map stitching based localization method [107] is developed. In this method a local map is formed for each component of the network using multi-lateration and MDS. Then map stitching is done using a core node from a map either using some critera or randomly. Here the core node is a speacial node choosen for map-stitching.

Kwon et. al. [108] proposed a new method of map stitching to prevent flip error in localization. The translation, rotation and reflection are done in the stitching transformation. The minimum stitching errors are achieved by reflection and reflectionless transformation is called flip ambiguity. If both the operation is observed it is called flip conflict. This method reduces the flip error and conflicts. MDS and multilateration are used in path construction for localization. Finally global coordinate is calculated using the reference coordinate.

B. Least Square (LS) Estimation

Path Loss Model [109] is used to localize the unknown node. In this model ratio of transmitting power and receiving power is considered to calculate the distance. The model of the path loss is given as follows.

$$P_r(d_i) = P_r(d_0) - 10.\eta.log(d_i/d_0) + X_\sigma \quad (1)$$

Where $P_r(d_i)$ is the received signal power and $P_r(d_0)$ is the received signal power at a reference point d_0, and η is the path loss exponent.

The path loss exponent is the only unknown for an environment. A path loss exponent is found when the unknown node's position can be calculated using the linear least square estimator.

A localization approach [110] based on energy efficiency is proposed. In this method, average energy reception of anchor is considered. Different power allocation shows a substantial effect on localization accuracy. The author claim that an optimal power allocation can reduce the localization error. A tetrahedron based semi-3D range-based localization method [111] computes the pairwise distance between nodes as well as anchors which form a tetrahedron. The volume of the tetrahedron is calculated with Heron's formula [152]. Then a transformation of the coordinate is done with transformation matrix in 3D points followed by linear least square estimation to find the unknown nodes. A comparison of different maximum likelihood based localization with non-convex estimation is proposed [112]. The non-convex objective function has multiple local minima of the ML estimator which is critical in problem formulation of the localization algorithm. The convex relaxation is used to optimize the proposed estimator. Second-order cone programming is used for non-cooperative localization and Semidefinite programming is used for cooperative localization. Both the methods consider path-loss and unknown transmitted power. They have shown that the method have a better result than the existing algorithms. Multiple source localization is proposed by Shen et. al. [113]. This method uses time of arrival (ToA) as measurement technique to localize multiple nodes. ToA measurement is modelled with mixed optimization problem. Further it is optimized with convex optimization and represented with a permutation matrix. Then the permutation matrix is modified, which further divide this problem to subproblems taking initial value from the convex optimization result, by which improve the localization accuracy. A cooperative method is presented taking Fisher information matrix (FIM) [114] using the NLOS bias model. After comparing the least square (LS), square range LS (SRLS) and square range weighted LS (SR-WLS) algorithms position error bound (PEB) method, it is found that the SRLS and SR-WLS perform better.

C. Semi-definite Programming (SDP)

A range based maximum-likelihood (ML) algorithm is proposed by Oguz-Ekim et. al. [120]. The location estimation is done with maximum likelihood method followed by optimization using SDP (Semidefinite Programming).

D. Maximum Likelihood Estimation (MLE)

Maximum Likelihood method using cognitive sense estimation (C-ML) with the received signal strength indicator (RSSI) is proposed [115]. This method finds the environment whenever it is homogeneous or heterogeneous followed by a hypothesis testing of generalized likelihood ratio test (GLRT) [153].

The efficiency of the maximum likelihood estimator is enhanced by acoustic energy based localization [116]. Acoustic noise corrupt the source signal which is described by the correlation degree of degraded signal or Hurst exponent [154]. It is the level of the decay rate of auto-correlation coefficient function. Wavelet-based methods [155] calculates Hurst exponent of noisy signals. E. Dranka et. al. [116] proposed a source lcalization method. In this method each signal sample is represented by fractional Gaussian noise (fGn) which is capable of modeling any degree of correlation utilizing Hurst exponent and energy determination. The estimation process is called Hurst Maximum Likelihood Energy (HMLE) [116] localization. This estimator uses a gain matrix, attenuation matrix, acoustic energy source vector and error vector. From this estimator, the joint probability distribution is calculated, and log-likelihood function is formulated. This method performed better in noisy environment. Yin et. al. modified the ML estimator using expectation-conditional maximization (ECM) [117] criterion to estimate locations of the sensor nodes. This method models the measurement error as Gaussian mixture parameter. It is shown that the mobility information of the node has an impact on accuracy in localization schemes [118]. This algorithms first use RSS or ToA range measurement model and then uses ML estimator with different SDP (Semi-definite Programming) relaxation approach for non-convex objective function.Generally, SDP is used in noisy measurements. Simonetto et. al. [119] proposed a maximum likelihood based convex relaxation with certain novel characteristics.

E. Bayesian Ranging Model (BRL)

Bayesian Ranging Model (BRL) [121] uses ranging measurement using the Bayesian model. This method is a modification of Empirical Bayes model [156]. BRL method uses a minimum mean square error (MMSE) estimator for final estimation of conditional mean which includes shrinkage factor for correction of measurement. Iterative least square is used for position estimation and inclusion of shrinking factor makes a robust method.

F. Monte Carlo Localization (MCL)

The node position is estimated using the current beacon and historical beacon [126]. It consists of three phases; In first phase the intersection region of one-hop anchor node with historical anchor node is estimated. The area covered by the target is called constrained region. In second phase invalid samples are filtered out by RSS based constrained region. There may be three types of region Current-Current RSS constrained region (CC-region), Current-Historical-RSS constrained region (CH-region) and historical-historical RSS constrained region (HH-region). Finally, the location estimation is carried out by taking the centroid of all the valid samples.

Priyantha et. al. [47] introduced a distributed anchor-free scheme considering fold freedom of nodes. After every global translation, there is a proper orientation of the nodes called fold free graph. Anchor free localization (AFL) solve the false minima by construction and fold free contour of the nodes. Then a mass-spring optimization technique is applied. It is more accurate and converging to local minima.

G. Motion-Aware Self Localization (MASL) Technique

The distance between the mobile nodes in the mobile network changes over time. A dynamic estimation for measurement is proposed in MASL scheme [127] by Mirza et. al.

Estimating location of sensor nodes with propagation delay is complicated but MASL provides an accurate estimation. In this method the measured data are utilized in the post processing stage in a central station. The distance information is fed to an iterative algorithm. Each step the algorithm improves position information by dividing the area of operation with smaller grids with a higher probability of node presence. MASL is anchor-free and computationally simple. Online monitoring and synchronization are its principal drawbacks.

H. Hyperbola-based Localization (HL)

The traditional source localization problem is adapted for two-dimensional underwater acoustic WSNs [128] [129]. The computation is based on hyperbola-based estimator [128] [129]. In HL systems a long range signal is sent to central node by the unknown nodes. Then the central node estimates the location of the unknown nodes. It consumes excessive energy due to use of long range signals. The anchor nodes are placed in the corners of the network so it cannot be extended into three-dimensional sensor network.

I. Area-based Localization Scheme (ALS)

Yao et. al. [130] proposed the area based localization schemes which is further modified for stable two-dimensional underwater acoustic WSNs by Chandrasekhar et. al. [131]. ALS is a coarse-grained localization method which yields an estimated area where the node present in contrast to the exact coordinates of the sensor node. Here anchor node partitioned the area with non-overlapping areas by sending different power level. Anchor nodes listen to each others signal keeping the list of anchor nodes with power level and send the data to sink node. The sink associates the position of the anchor nodes so it can estimate the position of the unknown nodes. It is applicable when anchors can modify their power levels. It is range free, computationally simple and non-synchronized. This method does not apply for online localization estimation. In this method the unknown nodes send the location information to sink node. Hence, it has high communication cost with high energy loss.

J. Three Dimensional Multi-power Area Localization Scheme (3D-MALS)

Zhou et. al. [132] extended the ALS method further in three-dimensional sensor network called 3D-MALS. 3D-MALS method is a combination of vertical mobility method [137] and variable transmission level method [131] of the anchor nodes. In underwater wireless sensor network there is an elevetor like special transceiver called Detachable Elevator Transceivers (DETs) [132]. The DETs broadcast their location information with varying power level and continuously descend in water. The unknown node receives anchor position and their respective lowest power. Further the unknown node send the position and power level of the anchor nodes to the sink node. Sink node calculates the area of the unknown nodes by the power level and location of anchor nodes. Since all unknown node communicate to sink node the communication cost is very high in this method.

K. Collaborative Localization (CL)

Mirza et. al. [133] proposed a prediction-based Collaborative Localization (CL) method for mobile wireless sensor network. This method is applicable for terrestrial and underwater wireless sensor network. Underwater WSNs collect information from the depth sensor nodes and passes it to the surface sensor nodes. Profilers and Followers are two types of nodes present in this protocol. Profilers are deeper sensor nodes in underwater WSN which are localized with ToA technique. The location of the Profiler sensor nodes gives a prediction of the future location of the Follower sensor nodes. The Follower sensor nodes are drifting with the water current similar to Profiler sensor nodes. Here the author assumes the underwater wireless sensor network descend with constant velocity. The problem of this type of network is synchronization.

L. AUV-Aided Localization (AAL)

Erol et.al. proposed AUV-Aided Localization (AAL) [134] for three-dimensional hybrid underwater sensor network. AUV is a vehicle which can find its location by dead-reckoning. This is expensive navigation tools and need frequent calibration with the help of GPS. The AUV broadcasts its location information while moving under water. The unknown sensor nodes receive the AUV location. From three consecutive broadcast messages, unknown sensor node estimates its location using lateration. It is a two-way ranging method so donot need synchronization, but the energy consumption is more.

M. Localization with Directional Beacons (LDB)

The LDB [135] [136] is a three-dimensional hybrid method proposed by Luo et.al. similar to AAL. It has application in an underwater sensor network. In this method the AUV is first localize itself with GPS then move to underwater for dead-reckoning. This approach is different from AAL in the sense AUV uses directional acoustic transceiver to broadcast its coordinates and angle. From the angle information, the unknown node calculate location. It is a range free method and more energy-efficient than AAL method.

N. Dive and Rise Localization (DNRL) Protocol

DNRL is a mobile anchor based localization where anchor nodes are called DiveNRise (DNR) beacons. The anchors can move up and down in underwater sensor network with the hydraulic principles and help the unknown nodes to localize themselves [137]. Anchor nodes are enabled with GPS and find their location when floating to the surface and then they move to a pre-calibrated depth broadcasting their location information. The unknown nodes listen to the broadcast messages from the anchor and utilise ToA to calculate their positions using lateration as shown in Fig. 15 (a). The advantage of this method is high energy efficiency and low communication overhead. The drawback is use of ToA which need synchronization.

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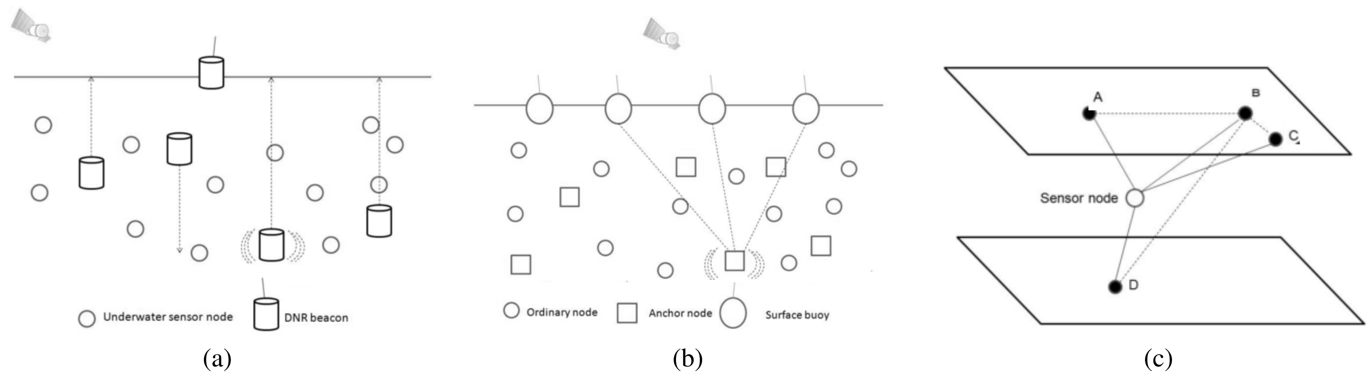

Fig. 15. Application Scenarios (a)DNRL method (b)LSLS Method (c) TDoA measurement used in UPS Method

O. Multi-Stage Localization (MSL)

Erol et. al. proposed a Multi-Stage Localization [138] method. It is the extension of DNRL [137] method by promoting the localized nodes as anchor nodes. First unlocalized node estimates its location with distance measurement from three non-co planner anchor nodes. Then it is promoted to anchor nodes and help other unknown nodes to localize. The drawback of this method is high communication overhead due to an iterative process. Hence this approach is less power efficient than DNRL. Propagation of error is added in this method.

P. Large-Scale Hierarchical Localization (LSHL) Protocol

Large-Scale Hierarchical Localization (LSHL) Protocol is proposed by Zhou et. al. [139] for underwater wireless sensor network. This network contains three types of nodes: Surface Buoys, Anchor Nodes and Sensor Nodes. Surface Buoys have GPS receiver and they localize themselves with line-of-sight satellite. Anchor nodes find localization through surface buoys and move underwater in the network. The common sensor nodes determine their location from the mobile anchor nodes with the help of ToA method. When the anchor is two hops away the non-localized node find its position from the extended Euclidean distance estimation algorithm [139]. Key issues faced by this network is high energy consumption and high communication overhead compared to DNRL and MSL. The method presented in LSHL [139] with Surface Buoys, Anchor nodes and Sensor Nodes are further improved with SLMP [151] method proposed by Zhou et. al. Mobility patterns and sequential position information help anchor nodes to estimate their current location. Anchor periodically check the patterns since it can obsolete in due course of time. When the pattern is not valid anchor updates the pattern. Surface Buoys localize themselves with GPS and transfer location information to anchor nodes. After prediction, the anchor node use Surface Buoys coordinate and distance information to estimate its location. If the discrepancy within predicted and estimated location is smaller than the threshold then the mobility model of the anchor is assumed to be valid. When it is not valid, it will run mobility prediction algorithm to determine new mobility pattern. The common nodes predict their location using the mobility pattern and it is expected to be true until a further update from the anchor. Communication cost and energy consumption depends upon the pattern of the mobility.

Q. Detachable Elevator Transceiver Localization (DETL)Protocol

DETL [140] method proposed by Chen et.al uses the same architecture as LSHL [139] method with an extension of eliminating anchor localization. Surface Buoys estimate their location from GPS. DET units moves up and down with broadcasting coordinates at several depths alike to DNRL. DET coordinates and distance helps localize anchor nodes. Normal sensor nodes are localized like LSHL. DETL is a solution for anchor localization for deep and narrow nodes with the help of broadcasting short range acoustic links. Major drawback is the requirement of number of DETs.

R. Three-Dimensional Underwater Localization (3DUL)

For hybrid underwater sensor network an iterative localization method is presented by Isik et. al. [141]. The localization process starts with the surface anchor nodes that receives location from GPS transceiver. The surface anchor nodes broadcasts its location information to the next sensor node in one hop distance. The sensor nodes receive position information of anchor nodes, estimate their position with two-way ToA estimator and further promoted to anchor nodes. This method repeats until reach the last layer of a network similar to MSL and LSHL. The drawback of this approach is localization delay of the lower sensor nodes and error propagation of the estimated sensor node from top anchor nodes to bottom unknown nodes.

S. Anchor-Free Localization (AFL)

Anchor-Free Localization [157] is proposed by Capkun et. al. for WSNs. This method is extended to underwater sensor network by Othman et. al. [142] [143]. Here the author proposes the concept of the seed node (S). Localization starts with node discovery process initiated by seed node (S1). S1 broadcast its position and receives the distance information from the neighbor nodes. Then second seed node, S2 is selected from the neighbor nodes. The same process is repeated. The distance of the new seed is broadcasted by

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other seeds when a new seed is selected. The intersection of three seed forms an area, and the sensor present in the area find its position with trilateration. This method forms a local coordinate system in the process of localization. This approach faces high energy consumption, communication overhead and propagation delay.

T. Underwater Positioning Scheme (UPS)

Cheng et. al. [144] [145] extends the terrestrial positioning scheme for localization to underwater scenarios. UPS is a localization method based on TDoA scheme. This approach uses four anchors which sequentially broadcast beacon signal. One is picked as a master anchor and broadcast beacon and other anchor receive the beacon with timing information. Then a sensor node receives the information of the beacon packet of the anchor and estimate their position using TDoA and trilateration method as shown in Fig 15 (c). This method is less energy consuming with low communication overhead. This approach cannot localize if sensor node is outside the area enclosed by four anchor nodes [144].

U. Wide Coverage Positioning (WPS)

The UPS method presented before [144] is unable to localize sensor nodes found outside the area enclosed by the four sensor nodes. This problem is solved by Tan et. al. [146] with using one more anchor node. WPS localize with four anchors called UPS (4) when localizable and when not localizable it localize with five anchor nodes called UPS (5). UPS (4) and UPS (5) combined work to localize the network and reduce communication overhead for nodes those are localizable with four nodes. The energy consumption in this method is same as in original UPS [144] method. The drawback of this system is localization delay.

V. Large-Scale Localization Scheme (LSLS)

The coverage of UPS [144] is increased by augmenting iterative localization phase and complimentary phase is called LSLS [147] proposed by Wang et.al and explained in Fig 15. (b). Initially, the underwater nodes localize using UPS. The next phase is iterative localization phase. The localized nodes in the first phase are promoted to anchor nodes and assist in localizing other nodes. The last stage is the complimentary phase. In this step unallocated nodes start a localization request selecting a set of reference nodes and repeat UPS method. The advantages of UPS are inherited by LSLS. Coverage is increased by iterative phase and unique localization is raised in complimentary phase [146]. LSLS method has greater communication cost and energy loss than UPS since two more stages are attached.

W. Underwater Sensor Positioning (USP)

For three-dimensional underwater network USP [148] [149] [150] is proposed by Teymorian et. al. This method assumes that all sensor node know their depth information by pressure sensor. Considering the depth information an unknown node find the available anchor nodes in the horizontal plan in which it is situated. It maps two dimensions from three dimensions. There is a chance of overlapping location of anchor nodes. If overlapping anchors presents, then the unknown node picks another collection of anchor nodes. In each repetition of USP the nodes which are already localized show their location messages and improve their location information accepting neighbor location messages. If only two anchors available in neighbor it uses bilateration which may not find unique location. In this case the sensor wait for another localized anchor message. The drawback of this method is all nodes should be synchronized.

X. Other Estimators

Gepshtein et. al. proposed a novel method of localization considering dual embedding spectral regression (DESR) [122]. Lasla et. al. [124] proposed a half symmetric lens (HLS) method using RSSI information exchange. In this method a pair of anchor forms a symmetric lens shape. Further it is divided into two halves and ensure if unknown node is inside any of them using RSSI. Then the unknown node is estimated with the help of grid scan. A distributed fingerprint based method [125] follows accelerometer data for better accuracy. In this method area is partitioned and RSSI fingerprint is used to form local map followed by estimation of nodes using nearest neighbour (NN) [158]. After this the local map is converted into a global map. The estimation accuracy is improved by considering mobility information of some selected nodes.

Y. Summary and Insight

It is not always possible theoretically calculate the position geometrically. There are constraints in different network and infrastructure. Hence statistical approximation of location based on existing data are required. Huge volume of methods in the literature are reviewed and classified. The accuracy of the method depends upon the range measurement. The better is the range measurement the estimation output is accurate. So from reviewing the literature it can be concluded that the accuracy depends upon range measurement techniques. Another aspect of this estimator is that the distributed algorithms propagate localization error. Hence centralized algorithms are suitable for IoT infrastructure.

VIII. Fingerprinting

The localization based on fingerprint approach takes a signature and match it with a set of geo-tagged signatures to find the position of the device. In the device, the signature can be recorded using various sensors. The user's activity patterns can be detected using intelligent sensors. For visual signature, the camera is used to capture an image of the landmark and resemble it against the geo-tagged image to identify the location. Similarly, the audio signature can be detected by a microphone. The WiFi can be used to get the signature and find the movement pattern of the devices. The main aim of fingerprint-based localization is to match the signature and efficiently localize a device. This can be further classified as follows.

TABLE VII
FINGERPRINTING APPROACH OF LOCALIZATION

Fingerprint Model	Algorithm	Sensor Measurement	Accuracy	Power Consumption	Remarks
Signal Pattern	PWF [159]	RSSI peak in a temporal sequence	Medium	Medium	Peak detection and location estimation is difficult if the user movement is fast
	Walkie-Markie [160]	RSSI sequence	High	Low	For accurate data collection the user must move in one direction.
	UnLoc [161]	Wi-Fi Landmark	Medium	Medium	This approach is applicable best with dense landmark since the size of wifi landmarks cannot be too large
	HALLWAY [162]	Order of Wi-Fi RSSI value	High	Medium	The granularity of using received signal order may not be very high; the RSSI order remains similar at times.
	Wi-Fi signal Coverage Intersection and Division [163] [164]	Simillar signal values from signal sector within sector intersection	Low	High	If Wi-Fi AP installation are co-located, the overlapped region could be too large and may not provide tight constraints.
	Place Lab [165]	WiFi Antenna GSM Antenna	15 to 20 m	Medium	
	Place Engine [166]	WiFi Antenna	5 to 100 m	Medium	Very less response time less than 1 sec.
	P.Cherntanomwong [167]	WiFi Antenna	less than 5 m	Medium	
	CAPS [168]	GSM Antenna	Not Available	Low	
	CellSense [169]	GSM Antenna	27 to 42 m	Medium	Highly energy saving method 6 times than Signal Fingerprint Approach
Collaborative Pattern	VC [164]	Wi-Fi direct Bluetooth	Medium	Low	For absolute positioning distance measurement may not be very accurate.
	PA [170]	Sound Estimation	High	High	Require accurate pairwise distance measurement.rigid network graph may suffer from measurement error and require synchronisation
	Centaur [171]	Sound Estimation	High	High	Peer synchronization required design for static device.
	ZCL [172]	ZigBee	Low	Medium	The user must be near to each other, cannot provide randomly moving user.
	Social-Loc [173]	Wi-Fi direct Bluetooth	Low	Low	Thresholds of detection may experience from the noise and information using RSSI may not be accurate.
Visual Analysis	G.Schroth [174]	Camera	Less than 20 m	Medium	Close to Realtime
	J.Zhang [175]	Camera	Within 50 m	Medium	Percentage of accuracy is more than 96 percent.
Motion Analysis	Zee [176]	Auto Correlation based Step counts Heading direction	Medium	High	Employ map information to separate incorrect particle crowdsourced signal data may carry noise.
	XINS [177]	Peak detection based Step counts heading direction	High	High	Utilize particle filter to fuse different signals. Work the best when mixed signals are available for location fixing.
	Graph Fusion [178]	Peak detection based Step counts heading direction, online stride length estimation.	Medium	Medium	Analyze the indoor map model.
	HMM Fusion [179]	Step counts. heading direction	Low	Low	Extensive training data set required for HMM training which is expensive.
	Moloc [180]	Auto correlation based Step counts crowdsourced motion profile.heading direction	High	Low	Need to accumulate user motion profile for localization.
	MapCraft [181]	Step counts,Heading direction.	Medium	Low	Rely on extensive training sets; Complex training
	GAC [182]	Compass. Accelerometer	Within intracity	Low	Less use of GPS
	CompAcc [183]	Compass Accelerometer	Less than 11 m	Low	For fallback mechanism AGPS used.
	APT [184]	Gyroscope Accelerometer	Less than 5m	Low	GPS is infrequently used
Hybrid Model	M. Anisetti [185]	GSM Antenna, Camera	25 to 38m	Low	
	WhellLoe [186]	Accelerometer, Magnetometer, GSM Antenna	Less than 40m	Low	Localization estimation delay is very less, less than 40 ms .
	Dejavu [187]	WiFi Antenna GSM Antenna, Accelerometer, Magnetometer	8.4 to 16m	Low	Both energy efficient and highly accurate
	EnLoc [188]	WiFi Antenna, GSM Antenna	Less than 12m	Low	
	RAPS [189]	Accelerometer, GSM Antenna	Not Available	Low	Manually activated GPS
	Location Study [190]	Accelerometer	Not Available	Low	
	SmartLoc [191]	Gyroscope, Accelerometer	Less than 20m	Low	Special driving pattern used when GPS is weak.
	A. Hallquist [192]	Camera, Accelerometer, Compass	Less than 10m	Low	An extension of J.Zhang [175]

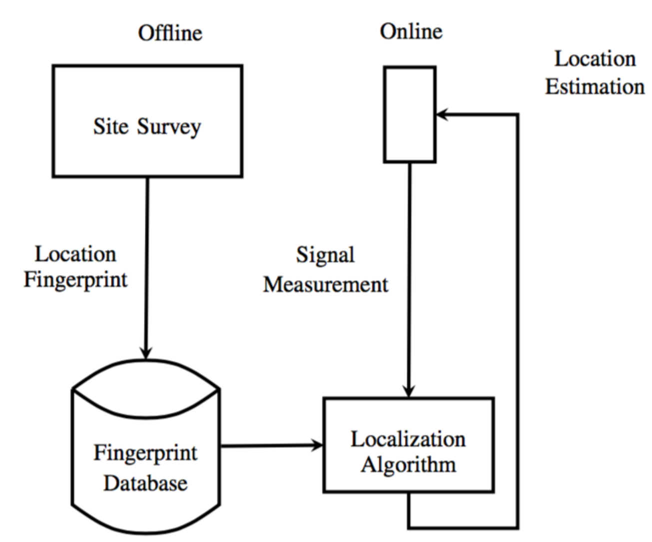

Fig. 16. Fingerprint Based Localization

A. Signal Pattern

Signal pattern based fingerprint localization method depends on the RSSI vectors. Measurement inaccuracy leads the target map wrongly into a different position. Higher accuracy can be obtained by considering both temporal and spatial pattern. Temporal pattern is signal sequence pattern during the movement in indoor area. Signal pattern of the route is used to find the location as compared to single signal vector. Spatial pattern is geographical distribution of signal or simply RSSI.

Peak based Wi-Fi Fingerprinting (PWF) [159] takes the highest signal state for estimation. The highest in the signal sequence informs the Wi-Fi access point is near to the sensor node. So powerful RSS gives tremendous determination than weak RSS. To find the highest a user have to collect a sequence of RSS values then it finds the corresponding signal map and highest RSS. The PWF method find accurate location when access points are on the ceiling of indoor path.

Taking the entire distribution of data for analysis is better than a particular peak value in case of a noisy environment. Walkie-Markie [160] take the whole signal sequence for classify the location. Wi-Fi RSSI patterns are first recorded in Walkie-Markie. For a given area the distribution of RSSI forms a pattern. By resembling users RSSI distribution throughout walking, Walkie-Markie finds the position and outline the knowledge of the target. In the indoor localization the Wi-Fi access points are placed at specific points. Excellent signal is received at some points, which is called landmarks. With some

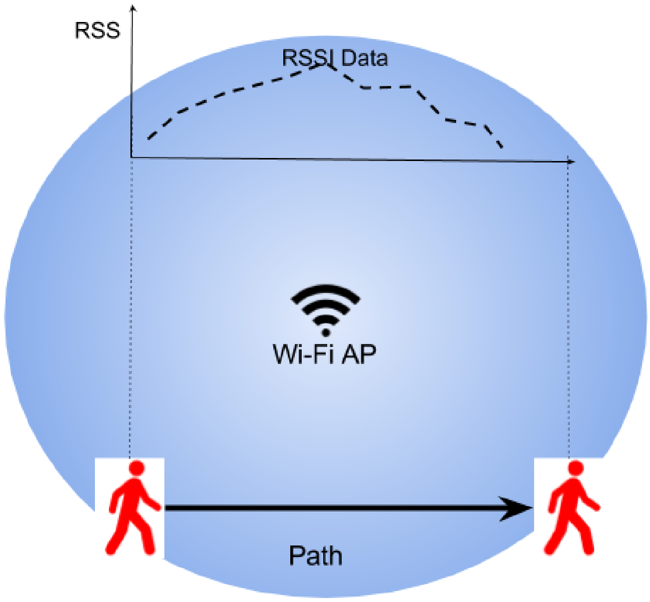

Fig. 17. Signal Pattern for Fingerprinting

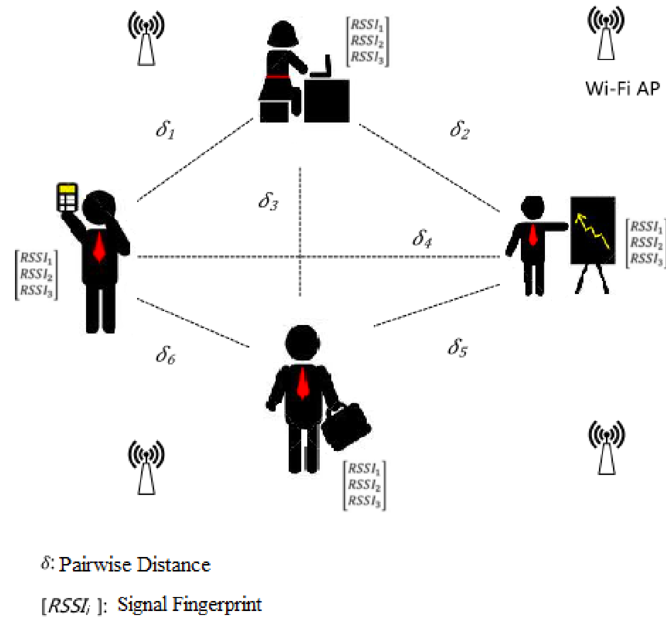

Fig. 18. Localization approach with collaborative pairwise distance measurement from WiFi signal RSSI.

simple investigation, these landmarks are saved in a database. UnLoc [161] and MapCraft [181] use this measurement of access points to correctly localize. These two methods contain stationary sensor and motion information of signal patterns. Simultaneous analysis of all the Access Points are considered to reduce measurement errors. HALLWAY [162] method classify signature pattern from different access point based on the signal strength. Device dependent small signal fluctuation is reduced by RSS distribution which indicates the location of the region. In indoor area when signal pattern is same this method is unable to localize. So the fingerprint is to be thoroughly preprocessed to obtain robust variation of location pattern. The intersection of signal pattern from various access points are analyzed for estimating the target [163]. The estimation error is reduced using the probabilistic approach of signal pattern [164]. The target is first outlined to the whole area of a fingerprint, and then the system determines the connecting point with maximum comparable signal patterns as position estimation. Temporal and spatial patterns can be used in indoor localization with good AP coverage [161] [159] [164].

B. Collaborative Pattern

Recently many works are carried out on collaborative localization. It is evolved from the context of social interactions like people may gather in social scenarios [172]. Social interaction shows a location pattern. Currently various mobile devices and sensor can easily discover their neighbors with the help of different protocols like bluetooth, Wi-Fi Aware, Wi-Fi direct [164], Near Field Communication (NFC) [173] and sound wave [170]. Depending upon the mutual distance measurement the collaborative localization is classified into two sections: distance-based and proximity-based algorithms.

1) Distance Based Scheme: Advanced sensor technology measures the pairwise distance between the user. From this pairwise distance the topology is constructed for different users. Then all the involved user's position is estimated in the distance-based method. Virtual Compass [164] proposes a new algorithm to locate neighbor users. It is used on Wi-Fi Direct and Bluetooth. This method is just an extension of Vivaldi algorithm [193] which find the coordinate so that all nodes provide pairwise distance. All the pairwise distance was given, and Vivaldi algorithm just forms a network and construct the network topology. A new approach called sound-based scheme [194] [195] to distance measurement. Peer-assisted (PA) localization [170] and Centaur [171] are the two basic works using the sound assisted localization are proposed. The distance measurement is done with Beep [194] technique. Mutual distance and Wifi RSSIs are collected by PA localization method. Initial location estimation is done with the traditional fingerprint of Wi-Fi signal of the user. The network topology is formed with this pairwise distance. The location of all users are estimated by PA localization method. Collaborative Localization using the Bayesian network is proposed by Centaur [171]. The rigid graph is not relied on Centaur's method as it is vulnerable to significant error in measurement. Instead it used the maximum likelihood of all associated devices. This method is only applicable for the static devices. Pairwise distance is not giving accurate result in the noisy environment as well as in the case of mobility, So proximity [172] based method is proposed. Proximity is not a fundamental concept, so the probabilistic inference is used for better estimation.

2) Proximity-based scheme: There are many shortcoming in the joint distance measurement of actual measurements. For dynamic measurement, proximity is often utilized. Proximity information is obtained from Wi-Fi AP list or MAC address or Bluetooth [196]. ZigBee-based collaborative localization (ZCL) [172] is a fine-grained system for absolute location

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estimation. ZCL first uses its neighbour-detection sensor with its radio and then it computes a confidence score for the target within the neighbor. Through the algorithm the system corrects the neighboring estimations meant on the contrast among confidence counts. The candidates with low confidence filtered out. The drawback of this system are it can undergo multipath impact, and the neighborhood knowledge can be inaccurate. This problem can be rectified using multiple samples and averaging filtering in ZCL. ZCL performs best when the users are in a small region or moving uniformly. Social-Loc [173] method propose a localization in random movement environment. It observe the signal patterns during the encounters like the two user crossing each other. Then it uses these encounters to correct the localization errors. First traditional fingerprint based localization is initialised with each user estimate multiple reference points with different prior probability. This collaborative localization method shows the highest accuracy.

C. Visual Analysis

The main underlying concept behind visual fingerprint analysis based localization is to match the user generated query image with the image from the geo-tagged database. The main drawback of this method is that when the size of fingerprint database increases the comparable algorithm performance decreases in terms of accuracy, high latency, and energy efficiency. Many solutions are proposed for this problem. Extensive range image retrieval for user localization is proposes by Zhang et. al. [175]. This approach divides the large database of geo-tagged images to overlapping cells and uses coarse position estimation to reduce the search space. The query image only matched with images located in the area of interest which improve the search performance. Transmission of data between client and server is the major challenge for visual-fingerprinting based localization. The statistics of the database is exploited and important characteristics which contribute maximum information on localization is identified. It is used by Schroth et. al. [174] to avoid redundant image and network delay.

D. Motion Analysis

The motiion sensor in smartphone and embedded devices can detect movement of a mobile user. This method is highly noisy, and estimation of distance and position is often inaccurate. To overcome this difficulty several resolutions have been recommended by supplementing GPS module and synchronization by M. Youssef et. al. [182] of data from motion sensors. The main idea of reducing error is to turn on GPS module in some interval and synchronize GPS data with the motion sensor data. The trade-off is in between energy and accuracy. The more accuracy can be obtained by synchronizing the GPS module. This process require more power consumption. Experiment shows that the proposed method [182] is able to save energy of the system exponentially. An infrastructure-independent localization system [183] is built by CompAcc using DR algorithm and Assisted-GPS (AGPS). Speed and orientation of the device are measured by an accelerometer and an electronic compass. A dead-reckoning technique is applied with the measured data and estimate the pattern of path signature which is further united to form the whole path. This method is simple but consuming time in calibration of sensors. Hence it is not applicable for large-scale applications. Zhu et. al. [184] proposed Accurate Pedestrian Tracking (APT) method with high accuracy compared to GPS. APT uses map matching with a strong DR algorithm with error-tolerant method. This DR algorithm finds the acceleration pattern of the mobile device. Experimentally it is shown that APT is better than GPS. Motion assisted localization is an indoor localization which uses hybrid techniques. Recently the development of motion sensors in the mobile devices are very advanced, it further improved the indoor localization based on motion assistance. The recent advancement on motion assisted localization is explained as follows. The essential part of accurate motion-assisted localization is to monitor the movement pattern of the object. The major challenges are imperfect calibration and noisy measurement of the sensors. Hence the motion detection is the main aim of the motion-assisted localization. Magnetometer, gyroscopes and accelerometers are used for movement detections. These detection techniques are further improved by signal filtering techniques. For real deployment, the motion sensor requires specific calibration which can be offline [178], [161] or online [197].

The fusion of the detected motion are essential for the localization accuracy. The correlation like temporal or special between measured signal should be capture for fusion. The model should be computationally efficient, which is important for the motion-assisted localization [180] [181]. Finding the target location is the main focus for traditional fusion method [178]. The incorrect position is filtered out with fusion filters which filter signal fluctuation or fingerprint ambiguity. Some recent works on fusion methods are given below.

1) Kalman filter: Kalman filter (KF) [198] is used in discrete time system. Under linear Gaussian environment Kalman filter obtain a better result than least square estimation [199]. Kalman filter solves fusion problem for linear, and for nonlinear cases. It is extended to Extended Kalman Filter (EKF) [200]. Moreover, Unscented KF and Fingerprint KF (FKF) [201] utilizes the linear unbiased estimator by linking all the current and past signal ranges.

2) Particle filter: Particle filter is more generalized version of tracking methods based on nonlinear motion representation. Initially all the measured point are collected then inconsistent localtion points are filtered out comparing with walking distance. The computational cost of particle filter is very high compared to Kalman filter. Graph-Fusion [178] introduces a system which clarifies the predictions of particle filter. As applying several particles significantly raises the complexity [179]. The main focus on utilizing extra efficient fusion patterns to substitute particle filter. Zee [176] and XINS [177] are two standard works applying particle filter. Zee employs the map constraints to filter the particles and restrict the exploration region of target localization.

3) Advanced and expert fusion models: Recently some expert models are proposed [180], [178], [181] to locate the target by: 1) Simplifying indoor map formations [178] with minimum measured data 2) Analyze the localization estimate while performing adequate calculations using dynamic or clear probabilistic models. These model uses Hidden Markov Model (HMM) [179] or Conditional Random Field (CRF) [181]. The HMM Fusion [179] aims to apply Hidden Markov Model (HMM) to mix the sensor and interpret the fusion method. HMM requires extensive training data set and the offline training method is yet computationally complex [180]. Prior to HMM model, MoLoc [180] forms the probabilistic transition connecting diverse locations in the site based on the user's stepping length and direction. MapCraft [181], [202] proposed a system meant on Conditional Random Field (CRF) more complex than HMM.

E. Hybrid Model

The accuracy and energy efficiency of fingerprint-based localization is improved by hybrid schemes. This method always requires fingerprint generation process before localization. In fingerprint generation process sensed data are collected from multiple sensors to combine and construct the hybrid fingerprints. Different types of hybrid systems for localization are described as follows.

1) Use of Multiple Fingerprint Modes: The area where poor signal and low geolocation are present that can be enhanced by mixing location information acquired by RSSI with the landmark matching [185]. This method is designed on time-forwarding algorithm using a database association technique. Further it is improved by the landmark recognition technique proposed by J. Zhang et. al [175]. A sensor fusion approach using the GPS, accelerometer and compass is proposed by Hallquist et. al. [192]. This method first finds the image that resembles with the query image taken by the device from the database [175]. Then the suitable matched image and its global coordinates are used to improve the query image. Further, the position is computed with homography transformation matrix among the query and matching image. WeelLoc [186] is a continuous location service. It is an indirect method which uses mobility trace through interpolation or extrapolation and matches with the map via HMM and Viterbi decoding method. Dejavu et. al. [187] provides both energy efficiency and accuracy of localization of outdoor environment. The main idea of this method is based on the fact that different places have a different unique signature which is used to distinguish between them. This approach used dead-reckoning based techniques and proved that it is better in localization and energy efficiency than GPS.

2) Augmenting Standard Positioning Techniques With Fingerprints: Energy efficiency is a major concern for wireless sensor network localization system. Many solutions are proposed for energy efficient fingerprinting method. The Rate-Adaptive Positioning System (RAPS) is a novel techniques for energy and accuracy tradeoff [189]. RAPS maintain a localization history and velocity of the mobile nodes. When the accuracy is below certain threshold it turn on the GPS module. It uses duty-cycle based accelerometer and estimate the movement. This also uses Bluetooth connection to diminish position ambiguity among neighboring nodes. If RAPS detects location where GPS is not available then it avoids GPS to turn on the sensors. Experiments showed that battery lifetime in RAPS is 3.8 times longer than GPS. LocationStudy is another system which improves energy efficiency by accelerometer based method [190]. This method uses mobility discovery algorithm which detects mobility pattern and switch on or of the location sensors. Inertial sensors like accelerometer or compass are used to measure speed and direction of the mobile user and determine the location of the user using dead-reckoning algorithm [184] [183]. However, those sensors are extremely noisy and give errors in estimation. To reduce these noise and accumulated error, the SmartLoc [191] uses predictive regression model for estimation of trajectory. This method utilizes a self-learning paradigm which calibrates the localization event. It further improves the accuracy even with the weak GPS signal.

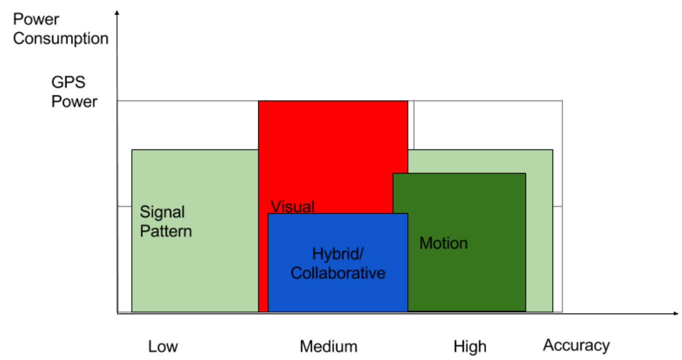

Fig. 19. Comparative plot of different Fingerprinting approach.

F. Summary and Insight

Accuracy and complexity of algorithms are two basis of selecting better algorithms. In IoT infrastructure it is complex to achieve both attributes. The limited power capability and computing power of IoT device with heterogenous nature of the device various challenges arises. A comparative study and analysis of fingerprinting algorithms on the basis of accuracy and energy efficiency is plotted. It is found that motion information based fingerprinting approach is better in terms of energy and accuracy and outperforms the others methods shown in Fig. 19.

IX. Stochastic Model/Markov Process Based Localization

A novel optimization method for decesion making in scenarios where uncertainty play important role is modelled with Markov Decesion Process. The interaction of the sensor nodes with environment can be modelled with Markov Decesion Process. The sensor node localization is carried out with different extensions of Markov Models [217]: POMDP (Partially Observable Markov Decesion Process), MMDP (Multi-agent Markov Decesion process), DEC-POMDPS (Decentralized Partially Observable Markov Decesion Process) and SG (Stochastic Game). This is shown in Fig. 20.

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TABLE VIII
STOCHASTIC MODEL BASED LOCALIZATION

Stochastic Models	Algorithm	Decision	States	Actions	Rewards/Costs	Application Context
POMDP	[203]	Centralized	Node Activation (sleep,active)	Select Active Nodes	Energy,Detection Probability	Cooperative Object Tracking
	[204]	Centralized	Estimated Object's Location, Sleep times	Select Active Nodes	Energy Consumption,Detection Probability	Cooperative Object Tracking
	[205]	Centralized	Targets locations, node activations	Select active nodes	Energy consumption, detection probability	Multiple Target Tracking
	[206]	Centralized	Estimated Object's Location	Select Active Nodes	Energy Consumption,Detection Probability	Cooperative Object Tracking
	[207]	Centralized	Targets locations and velocity	Select active nodes	Nodes interception risk,detection accuracy	Multiple Target Tracking
	[208]	Centralized	Human body activities	Select active nodes	Energy Consumption,detection Probability	Health and body Networks
	[209]	Centralized	Human body activities	Select active nodes	Energy Consumption and detection probability	Health and body Networks
MDP	[210]	Centralized	Estimated Adversary's Region	Select Active Nodes	Energy Consumption,Detection Probability	Cooperative Object Tracking
	[211]	Distributed	Sensor's State (sleep,fully or partially active)	Select Active Nodes	Energy ,Detection Probability	Clustered Tracking Systems
	[212]	Distributed	Targets Location and velocities	Send or discard a message	Detection probability	Prioritized data delivery
	[213]	Centralized	Asset's location	Move (north,east,west,south)	Transportation Delay	Health and body Networks
HMDP	[214]	Distributed	CH's state (Sensing,listening or tracking)	Select Active Nodes	Sensing Rate ,Detection Probability	Clustered Tracking Systems
CMDP	[215]	Centralized	(Lower tier) buffer occupancy,congestion matrix	Select active noes and detection threshold	Network congestion ,detection probability	Clustered Tracking Systems
			(Upper tier)priority matrix,competing user	Assign a spectrum	Priority	Clustered Tracking Systems
SG	[216]	Centralized	Quantized Spectrum Bandwidth	Select Active Nodes	Energy ,Sucessfull transmission	Cooperative Object Tracking

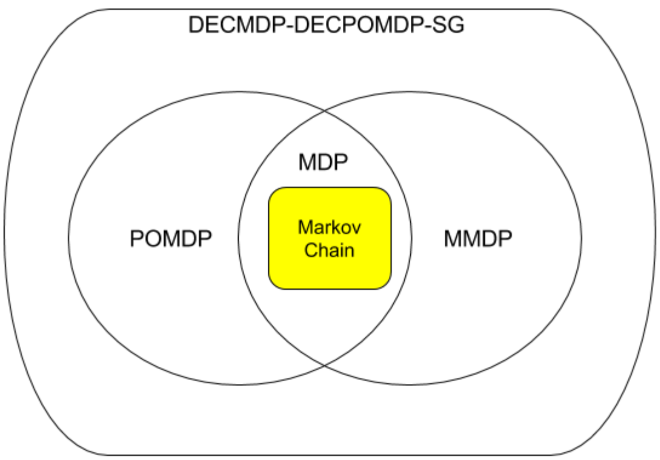

Fig. 20. Markov Models: MDP-Markov Decision Process,POMDP-Partially Observable Markov Decision Process, MMDP-Multiagent Markov Decision process, DECPOMDP-Decentralized Partially Observable Markov Decision Process, SG-Stochastic Game

When there is hardware limitation for sensor node's localization POMDP is applied. To apply POMDP the sensor nodes in the network has to maintain the history of the observed location. MMDP is applied when all the sensor nodes in the network cooperatively optimize to find the location. DEC-POMDP is similar to MMDP but sensor nodes localize a part of the network in individual step. It is a decentralized version of MMDP. SG is a non-cooperative method of interaction of sensor nodes for localization. The sensor node's objective in this method is to maximize localization accuracy individually.

A. Partially Observable Markov Decision Process (POMDP)

For the densely deployed WSNs the duty cycle management policy is presented by Fuemmeler et. al. [203]. There are two modes: sleep and active modes. The detection is done by only a few nodes so the other sensor nodes can be switched to sleep mode. The inactive sensor node cannot be active by any external signal. It will be activated after interior sleep timer. A minimum number of active nodes are mere in the network at any instant of time. This developed system is based on POMDP model [217]. Energy saving and location detection accuracy combined to form the cost function for optimize detection performance.

Atia et. al. [206] proposed the method considering the object tracking in overlapped and non-overlapped region. When many sensors detect the target, it is called overlapped and when a single sensor detects the target it is called non-overlapped. In both the cases energy and detection accuracy has a trade-off. Fuemmeler et. al. [204] proposed a method in which they are considering sensor location outside the coverage area. A central controller with POMDP manage the sleep and active time of the sensor node for the better target prediction.

The limited and shared channel spectrum and its effect on object detection are analyzed by Huang et. al. [216]. In this protocol spectrum bandwidth is managed by a coordinator, which consider only active nodes. Spectrum management is used for transmission decision and object detection. Further the above methods [210] [206] [204] are extended with a centralized offline learning method called Q-learning method.

Biometric sensor detects body activities. Biometric WSN collects biological data from different body activities with the help of biometric devices like electrocardiogram (ECG), electroencephalograph (EEG), pulse oximeters etc. The real-time tracking of the physical condition of the human body for disease monitoring is developed by Au et. al. [208]. Network lifetime is an issue for these systems since sensor selection and action requires continuous scheduling. POMDP algorithms are used for scheduling of real-time body area sensor of health monitoring system. Detection of the body activities and Energy consumption of the sensor network are two challenges. The model proposed by the authors considers human activities as a state space and various commands for sensor actions like active or sleep state constituted action space. Zois et. al. [209] developed activity detection in wireless body area network. The author considered a heterogeneous network and applied optimum node selection with sensor node sleep scheduling. Different human activities like standing up, running, walking etc. are considered and POMDP is formulated. Further it is solved with dynamic programming to find the optimum selection. Switching between different activities is modeled with their probability as a transition matrix.

B. Markov Decision Process (MDP)

In monitoring applications, the localization of malicious objects is presented by Zhan et. al. [210]. The cooperating node finds the adversary location by MDP. MDP's states represents the possible detection area. The intersection of these detection areas represents the possible location of nodes. This method determines a set of nodes to be activated for the detection of the malicious object.

In surveillance systems, the target tracking is analyzed by Misra et. al. [211]. They proposed three modes of sensor node namely sleep mode, partially active mode (not processing), fully active mode (processing). The difference in partially active and fully active mode is fully active mode process the information. The wakeup request sent by cluster head to switch nodes to fully active mode. The secondary users are allowed to access the spectrum when it is not used by the primary users. Cluster head selects the minimum number of active nodes using MDP to optimize the energy. Each cluster head detects the objects based on the message received by neighboring clusters.

Pietrabissa et. al. [213] modeled a hospital system and formed a tracking system of various medical assets with radio-frequency identification (RFID). Since it is an indoor application, so the RFID signals have affected by walls and other scenarios. WSN collects information from a deployed region and sends it to the sink. The network life can be improved by sending data those are important and dropping the data which are unimportant for localization. So this can be formulated as maximizing the probability of sensitive data delivery and dropping of useless data. Pino-Povedano et. al. [212] proposed a method for dropping the data which are unimportant for target tracking. The author proposed a method to select the data to be declined by the importance of the message power consumption in the node and transmission link cost. On successful transmission of the data from source to the sink one unit of reward is given and feedback is sent from sink to source. Feedback, on the other hand, increase the data load of the network. Hence, this work is further extended for suboptimal feedback based on two hop.

C. Hierarchical Markov decision process (HMDP)

Resource availability is the main consideration for object detection and tracking in cluster-based systems. Both special and temporal characteristic of an object is detected by a target tracking algorithm presented by Yeow et. al. [214]. The agents are divided into Lower level agent (LLA) and Higher Level Agents (HLA). LLAs predict the target location followed by activation of HLAs. HLAs are cluster heads with sleep, sensing, tracking and listening states. When HLAs are active they track objects. If one HLA gets information about neighbouring HLA tracking object, it switches to listening state.

D. Constrained Markov Decision Processes (CMDP)

Detection in Cognitive Radio WSNs is proposed by Jamal et. al. [215] using two tier CMDP model. The system offered to be better in detection accuracy, managed the network congestion and spectrum allocation. It has two tier system architecture. The cluster head consists of upper tier which passes the messages to the base station. Secondary user consist of the lower tier. This model balances accuracy and network congestion. The sensor node detects delay and passes it to the cluster head. The upper tier manages spectrum access by considering event arrival rate, link quality, services priority and collision probability.

E. Summary and Insight

Existing literature shows that both finite time and infinite time markov decision process can be solved in polynomial time. Extending markov decision process in different scenarios leads different complexity. The complexity of markov decision process is P-Complete as well as of MMDP and POMDP. But DECMDP and DECPOMDP are further more complex. Hence in stochastic modelling the worst case complexity plays a major impact in application scenarios. Majority of this methods are applied in object tracking systems. Among all POMDP method have huge application in the literature like cooperative object tracking, multiple object tracking, health and body monitoring due to its low complexity and centralized applicability. Hence it can be suitable for IoT infrastructure.

X. Machine Learning Approach

Localization using learning algorithms are not highlighted in many studies. Learning based localization uses a distance measurement matrix which is mostly RSSI and a learning algorithm. A comparative analysis is presented in Table IX. The noise like multipath, non-line of sight and fading impairs RSSI measurement. The noise is modeled with log-normal shadowing model (LNSM). The measurement with noise model is applied to learning-based optimization to predict the noise-free measurement of the range. Training and testing of these learning methods reduce the channel impairments.

The traditional approach uses LNSM-based distance estimators. These methods are simple but prone to channel impairments. The advantages of this approach is that it uses very less anchor nodes for static anchor. In case of mobile anchor nodes a single anchor node is sufficient to localize the network. Various learning methods like PSO-ANN uses multiple anchors to improve the distance estimation. Normally sensor nodes are deployed in a region where the supply of energy is restricted. The node simply use a battery and when the power is drained out the sensor lose its sensing and communication ability. So various strategies are developed for energy saving. One of the best methods is transmission power control (TPC). This method is based on the distance between sensor node and anchor node. The transmission power is reduced with respect to distance between anchor and sensor to save the energy.

The degree of interest in various scientific studies related to location-based services gained importance recently. A method using RSSI and linear least squares (LLS) was conducted by Yaming et. al. [109]. The LNSM path loss model generates the RSSI values. In this method the estimated distance error was found to be 2.72 m. Another method based on LNSM and Polynomial Modelling with a mobile anchor node to generate RSSI values is conducted by Pratap et. al. [232]. In this approach, the positional error is found to be 2.2m.

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TABLE IX
MACHINE LEARNING MODEL BASED LOCALIZATION APPROACH

Machine Learning Model	Algorithm	Architecture/Framework	Estimation Metric	Estimated Parameter	Type of Study	Environment	Tested Area	Localization Error
BR	[218]	ZigBee (MICAz)	RSSI	Location	Simulation and Experimental	Outdoor	10m x 10m	0.6938m
RP	[219]	IEEE 802.14.4 (Crossbow IRIS XM2110CA)	RSSI	Location	Experimental and Simulation	Indoor	Room Contains 24x10 position	0.3m
GR	[220]	Access Point	RSSI	Location	Simulation and Experimental	Indoor	20m x 20m	1.298m
MLP	[221]	ZigBee (CC2431)	RSSI	Distance	Experimental and ANN Simulation	Indoor	5m x 5m	2m
RBFN	[222]	ZigBee (FT-6250/FT-6251)	LQI	Location	Experimental	Indoor	7.26m x 16.5 m	2.8m
FF ANN	[223]	Zigbee (IRIS)	RSSI	Location	Experimental	Indoor	24m x 10 m	Cumulative Error Calculation
	[224]	N/A	RSSI	Location	Simulation	N/A	100m x100m	1.1862m
	[225]	Simulation in MATLAB	RSSI and Hop Count	Distance	Simulation	N/A	50m x 50m with Transmission Range (25m)	6-7m
LMFF	[226]	MATLAB Simulation	RSSI	Location	Simulation	N/A	100mx100m and 300m x 300m	0.25-0.75m
	[34]	ZigBee (XBee S2)	RSSI	Distance	Experimental and offline ANN training	Outdoor and Indoor	65m (Outdoor) 46m (Indoor)	0.022m (outdoor) 0.208m (indoor)
BR+ GD	[227]	ZigBee (Telosb)	RSSI and LQI	Location	Experimental and offline training	Indoor	12.19m x20.12 m and 6.28m x11.28 m	1.65 m
BR+LM	[228]	N/A	RSSI	Location	Simulation	N/A	300m x 300m	0.49m
MLP+GR	[229]	N/A	Wavelet-based features (WBF)	Distance and Location	Simulation	Indoor	120 untrained data and 350 trained data	2m (distance)
BR+RP+SCG	[230]	ZigBee (XBee S2)	RSSI	Location	Experimental	Indoor	8m x 6.4m	0.87m
LM+BR+RP+SCG+GD	[231]	ZigBee (XBee S2)	RSSI	Location	Experimental and Offline ANN training	Indoor	5m x 4m	0.3m

Estimation of the position of the sensor nodes in wireless sensor network is calculated mostly with the use of lateration or angulation. The position of the sensor node is determined by three anchor nodes in two-dimensional sensor network using trilateration [233]. In the case of mobile sensor and anchor nodes the distance between sensor and anchor changes over time so this method is not efficient. The hop count (HC) algorithms can be used for estimation of the distance between unknown mobile nodes. However, the limitation is that the network should be uniformly distributed. The accuracy of this uniform network is dependent upon the hop density of the network. Irregularly deployed network localization with HC method causes inaccuracy with even high system cost. So for mobile sensor and anchor node based network, statistical localization methods like Kalman filter is more accurate in prediction of position. Kalman filter applies a recursive strategy for range measurement and variance error reduction until final convergence. The application of this method is limited to linear systems [225].

Numerous artificial intelligence techniques promised better estimation of position recently like PSO and ANN. Sensor node localization with two PSO algorithms is proposed by Kulkarni et. al. [234]. Mobile ad-hoc network (MANET) utilize first PSO to localize the objective and second PSO to converge the nodes around the target. This type of network-centric collaborative localization shows the efficiency of PSO Algorithms. Artificial Neural Network (ANN) based estimators gaining importance in recent years. ANN shows faster convergence speed. The cost of calculation is very low compared to other estimators [224]. Irfan et. al. [227] propose two neural network based algorithms, Gradient Descent and Bayesian Regularization for indoor application for mobile network. ZigBee utilizes RSSI and link quality indicator (LQI) for neural network training and testing. The results show that 1.65 m position accuracy can be obtained by this method.

Link quality indicator (LQI) [222] has importance in indoor robotic sensor network localization and uses three ZigBee sensor node utilizing feed-forward sensor network. The average positioning of sensor error on this robotic experiment is found to be 2.8 m. Positioning of mobile nodes in case of the indoor network by using Levenberg-Marquardt (LM) training based feed-forward neural network algorithms estimator is proposed by Gogolak et. al. [223]. In this method mobile node records RSSI value of five anchor nodes. Then these values are used to train the neural network. This method is found to be better than weighted k-nearest neighbor (WkNN) method. When five anchor nodes are used WkNN method shows a better result than ANN. In case of three anchor nodes ANN shows a better result than WkNN. Hence higher anchor shows a better result in WkNN. Further this gives high cost of the network deployment.

Chuang et.al [225] propose a new Neural Network based node localization method. In this approach, the RSSI values are collected by LNSM method. The distance of HCs are the shortest routes which are calculated by Dijkstra algorithm. This method compared with PSO and ANN localization methods and found out to be better than them.

A. Summary and Insight

In most of the learning based localization research, the distance accuracy or localization accuracy is unsatisfactory. It opens a new research scope for energy saving localization technology design which can reduce power consumption and increase network lifetime.

XI. APPLICATIONS, CHALLENGES AND FUTURE RESEARCH IN IOT INFRASTRUCTURE

With incorporation of modern localization techniques in IoT infrastructure several important and popular application evolved to form a smart world. Increasing the computing capabilities and incorporating artificial intelligence techniques to the device made them smart devices like smart phone, smart TV, smart wearable devices etc. Movement of mechanical devices with incorporation of artificial intelligence and modern robotic techniques makes them smart with augmentation of IoT. Incorporation of IoT makes the health services to be smart with better outcomes. The buildings becomes smart with addition of RFID tags and Bluetooth technologies to provide location aware smart spaces [250], [251]. The management and monitoring of traffic is possible with addition of LoT techniques and computational intelligence. The handling of electrical usages in application as well as self adaptation of electric grid made them smart grid is possible only through LoT. The evolution of the world of making it smart world by incorporating intelligent computational capabilities to solve problems demands location information. In this section we will analyze the technical aspects of different IoT applications and their need for location information.

TABLE X
APPLICATIONS, CHALLENGES AND FUTURE RESEARCH OF LOCALIZATION IN IOT INFRASTRUCTURE

Applications in IoT	Sensor Used For Localization	Challenges	Future Research
Smart Devices(Phone,TV,Wearable,Tablet)	GPS, Wi-Fi signal, Cell Phone signals, Bluetooth, magnetometer, barometer, accelerometer and cameras	Diversified accuracy and precision.	Smart World [235]
Moving Smart Devices	Camera, Speedometer, RF communication devices, RFID readers and optical measuring meters.	Simultaneous Localization and Mapping(SLAM)	Autonomous Driving [236], [237], [238]
Smart Health	3D X-ray [239], 3D ultra-sound imaging [240], 3D Magnetic Resonance Imaging (MRI) [241], and ComputerAided Tomography(CAT) [242] , hybrid RF[243]	High accuracy and Precesion	Health Monitoring and Microbots [240] [241]
Smart Space	Active and Passive RFID chips	power efficiency	Smart RFID Tagging , RF Energy Transport [244]
Smart Transportation		Networking of Transporting System	Autonomous Vehicle [245]
Smart Infrastructure	Electrical grid sensor, water quality measurement sensor etc.		Smart Grid And Smart Infrastructure [246]
Smart Monitoring	Temperature sensors, Humidity sensor, fire-alarm sensor, toxical gas and chemical sensors	Signal Coverage and Target Positioning	Cognitive Radio Sensor Network(CRSN) [247], [248], [249]

A. Smart Device Localization and Future Research

Formation of smart world or environment is possible with the smart sensor technology with location information. IoT devices like smart phone, tablets, smart watch, smart glasses, smart TV either directly or indirectly uses location information for better services. Diversified Accuracy and Precision are the major challenges as different IoT device use different accuracy measure. For example in indoor localization the requirement is few meters whereas in outdoor it is tens of meter. There are two types of sensor like RF location sensor and Mechanical location sensor used. RF sensor are GPS receiver, WiFi sensor, Cellular Signal Sensor and Bluetooth sensor. The mechanical sensor used are magnetometer, barometer, accelerometer, cameras and microphone. Heterogeneous environment and multiple sensors in devices demands location for different applications [235].

B. Mobile Device(Robot) Localization and Autonomous Driving

The smart world is possible with development of Robotic platforms of different size of ground robots or flying robots. The applications include smart manufacturing, security, aerial photography, smart health technology, military mission etc. Since every robot is moving so real time location information is required. There is a requirement of simultaneous localization and mapping(SLAM) in either 2D or 3D. The robots benefits from SLAM methods for smart navigation in 2D [252], [253] and 3D [236], [237], [238] scenarios. Camera, Speedometer, RFID sensors, and Optical sensors are basically used but for medical bots inside human body the camera sensor is preferred [254]. The number of sensor and type of sensor used depend upon the application.

C. Health Monitoring and Microbots

The localization in medical term is to find out the location of tumors, pain, bleeding, lesion etc inside human body. Other localization applications like availability of doctors, location of patients and their activity detection. Medical equipments and their interconnection over IoT to form a smart health system Locating peoples and objects in geolocation scenarios to extract patterns of biological information for better prediction in IoT healthcare system [255], [256], [257]. High localization accuracy is the requirement for health device and monitoring systems inside human body. The sensor used for localization and mapping of things inside human body are Ultrasound imaging [240], Computer Aided Tomography(CAT) [242], 3D Magnetic Resonance Imaging(MRI) [241], 3D X-ray [239] and hybrid RF[243].

Human behaviour recognition is gaining importance in IoT infrastructure [258]. The movement of human body parts changes in signal reflections which leads to variation of Channel State Information (CSI). Analyzing CSI data and comparing existing model human behaviour can be analyzed. This is possible with feature extraction from CSI data. These data can only be organized with geographical localization based fingerprinting and help in model development.

D. Smart RFID and RF Energy Transport

The smart world is possible with the smart RFID technology with passive and active tags. RF energy transport have huge application in IoT infrastructure. Trillions of RFID tags in indoor and outdoor scenarios have been implemented in IoT scenarios. RFID tags are expected to be deployed in almost all devices ranging from small indoor objects to smart building [259], [260] embedded with RFID readers. There are active and passive devices and which is further extended with RF energy transport technology[244]. These RFID based localization system can augment the existing geolocation scenarios with better accuracy.

E. Transportation System Localization and Autonomous Vehicle

The key enabling technology of smart city and smart world is the smart transportation system [245]. The fuel consumption and cost of transport is hugely improved by using location information of ground and air transports and utilized it with a better network model. Finding the relative position and speed information have huge impact on smart vehicular navigation system. These navigation information is helpful for assisting drivers by social event analysis [261] land use monitoring [262] smart public security [245] urban traffic planning [263] etc. For all these application localization plays an important role.

F. Smart Grid and Smart Infrastructure

The IoT infrastructure implemented in national level recently and to form it there are different services like electric smart grid, smart water system etc [264]. For smooth operation and managing resources localization play important role like detecting faults in smart grid [265], [246]. Sensor used for water quality monitoring or the load in grid the quantity of information is not usable without the sensor location information.

G. Cognitive Radio Network and Smart Monitoring

The smart monitoring of accumulate real time data such as temperature, humidity, fire alarm and toxic gas which require event driven communication generally yields bursty traffic [247]. Hence Cognitive Radio Sensor Network(CRSN) is a promising method for heterogeneous network like IoT. CRSN have two types of sensor nodes: primary radio and cognitive radio nodes. The primary radio have the right to use the frequency band. When primary radio is not using the band the cognitive radio can only use the frequency band with their cognitive ability [248], [249]. The CRSN improve the spectrum aware reliability, opportunistic energy efficient transport, real time cognitive reliable transport. Hence smart monitoring of real time data is possible with cognitive radio sensor network in future IoT applications.

There are various interactive discipline which combine cloud computing, fog computing, mobility and interaction among them to build smart IoT system. The role of localization is important in building this smart IoT system. The application of localization in emerging smart city, health monitoring, RFID tags, smart transportation system and cognitive sensor network system is analyzed in context of challenges and future research direction.

XII. Conclusion

In this review of localization algorithms, a comparative strategies are presented for broad application of localization technologies in different forms of network. The future of localization and its implementation for IoT is manifested. Recent localization technologies are analysed and a taxonomical model is presented based on IoT Infrastructure. The emphasis of classification is done based on the presence of offline training state in the algorithms. Various Comparison tables are given for different approaches. How everything can be localized and its futuristic application of IoT-based localization is justified. Different noise distribution and their effect on localization are exposed. Thus the use of localization has different approach for different scenarios.

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