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Localization Adopting Machine Learning Techniques in Wireless Sensor Networks

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Abstract—Monitoring of dynamic environments that change rapidly with time is the prime application of wireless sensor networks. This change of behaviour is reasoned to either certain external factors or limitation of system designs itself in unpredicted causality. To adapt such conditions, machine learning techniques are deemed to be beneficial in eliminating the need for unnecessary redesign. Moreover, the techniques based on machine learning encourages many practical solutions to maximize usages of resource and thus enhances the lifespan of the sensor network. In this paper, an extensive literature is furnished over machine learning techniques that are used to address the issue of node localization in wireless sensor networks (WSNs). Strengths and weaknesses of each of the proposed algorithm in literature have been analysed and evaluated against the problem it has been developed. A comparative table is also presented to guide future designers in developing machine learning solutions suitable for specific application challenges in localization.

Index Terms—Wireless sensor networks, machine learning, localization, clustering, data aggregation.

I. Introduction

A wireless sensor network (WSN) is generally made up of multiple sensor nodes typically of tiny size, low power and low resources. The sensor nodes deployed over target region basically capture data about their environment and collect it and forward sensed data to central units also known as sinks or base stations to process it further as required by the problem. These sensor nodes are equipped with variety of sensors, such as acoustic, thermal, chemical, pressure, optical and weather and have great potential for designing powerful applications.

Developing efficient algorithms for variety of sensor applications is a challenging task. Particularly, common issues which need to be addressed by researchers are data reliability, data aggregation, node clustering, localization, events scheduling, energy aware routing, security and fault detection. Machine learning (ML) as a technique for only artificial intelligence (AI) [1] was introduced in the late 1950's. But very soon this technique evolved in various dimensions and moved into algorithms and made it computationally viable and robust. Moreover, machine learning techniques have been used extensively for a wide range of tasks including classification, regression and density estimation in a variety of application areas such as bioinformatics, speech recognition, spam detection, computer vision, fraud detection and advertising networks.

Machine learning techniques are viable due to following working methodologies:

1) It develops computer models for learning processes and solves the problem of knowledge acquisition hence improves the performance of developed systems [2].

2) To improve machine performance, it develops computational methods to detect and describe consistencies and patterns in training data [3].

The process of estimating the spatial coordinates of nodes and components of a network is called localization. This becomes an important capability of a sensor network, as most of sensor network operations require the positioning of nodes [4]. Most of large scale systems utilize global positioning system (GPS) hardware in each node to localize itself. This is costly and need energy. Moreover, may not perform in indoor systems efficiently. Certain applications use relative location measurement and relative locations can be transformed into absolute ones [5]. To improve performance of localization based on proximity, additional measurements based on distance, angle or a hybrid of these methods can be utilized. Distance measurements are determined using variety of techniques like RSSI, TOA, and TDOA. Furthermore, angle of the received signal can be measured using compasses or special smart antennas [6].

The technical information about various range-based localization methods are detailed in [7]. In mobile sensor networks position of sensor nodes may get changed after deployment due to mobility of nodes.

Localization techniques employing few anchor nodes using machine learning in sensor node can be summarized as follows:

1. Firstly, it converts relative positions of nodes to absolute ones using the anchor nodes and this way it eliminates the requirement of range measuring hardware unit to estimate distance.
2. For surveillance and object tracking and targeting systems, machine learning is used to partition the targeted area into number of clusters where each cluster specifies a location.

In this survey a different view of current state-of-the-art localization techniques using machine learning in WSNs are discussed and examined. Localization from the perspective of operation within a nonstationary environment is considered here. This is aimed at that this survey analyses the implementation of localization algorithms in a dynamic environment. In this work state-of-the-art of localization algorithms surveyed is presented and different techniques using machine learning are examined which can improve the performance considering the dynamic and distributed environment. Our survey aims to highlight current approaches to the localization problem based on learning, point out issues which are lacking, and recommend areas for future research.

The rest of the paper is organized as follows: Section II explains machine learning algorithms and themes that will be referred to in later sections. In Section III, reviews existing machine learning efforts to address functional issues of localization in WSNs. Here, an issue is functional if it is essential to the basic operation of the wireless sensor network. Section IV outlines contributions and open research problems for machine learning in WSNs.

II. Adoption of Machine Learning in Context to WSNs

Specifically, machine learning is used as collection of algorithms and tools to create prediction models. However, machine learning is beneficial as it has rich themes and patterns and thus provides tremendous flexibility benefits in context to WSNs. Some of the theoretical concepts and strategies for adopting machine learning in the context to WSNs is provided in this section. Existing machine learning algorithms are grouped into following categories:

A. Supervised Learning

The supervised learning uses a labeled training set to build the model and this model represents the learned relation between the input, output and system parameters. The major supervised learning algorithms which are usually used in WSNs are discussed here. However, supervised learning algorithms solves various issues in field of localization and objects targeting in [8-10], event detection and query processing in [11-14], media access control in [15-17], security and intrusion detection in [18-21] and quality of service (QoS), data integrity and fault detection in [22-24].

1) K-Nearest Neighbour (k-NN)

The supervised learning algorithm is based on classification of a data sample known as a query point based on the labels known as the output values of the near data samples. This way missing readings of a sensor node can be predicted using the average measurements of neighbouring sensors lying in specified diameter. There are numerous methods to determine the nearest set of nodes belonging to a sensor node. A simple method uses the Euclidean distance between different sensors. K-nearest neighbour method does computing relative to local points (i.e., k-nearest points, where k is a small positive integer) so it does not require high computational power. Moreover, appended with the correlated readings of neighbouring nodes makes k-nearest neighbour a suitable distributed learning algorithm for WSNs. The k-nearest neighbour algorithm performs efficiently in the query processing subsystem in most of applications of WSNs [11-12].

2) Decision Tree (DT)

This algorithm predicts labels of data by iterating sample data (input) through a learning tree [26]. In this processing, a comparison of feature property is made with decision conditions to reach a specific category. According to research literature available, DT algorithm has tried solving different design challenges of applications of WSNs. For example, based on a few critical features such as loss rate, mean time to failure (MTTF), corruption rate and mean time to restore (MTTR) DT identifies link reliability in WSNs very efficiently. However, this algorithm performs only with linearly separable data and building optimal learning trees is NP-complete [27] process.

3) Neural Networks (NNs)

This learning algorithm cascades chains of decision units i.e. perceptron's or radial basis functions and is used efficiently to identify nonlinear and complex functions [28]. The application of neural networks in WSNs in distributed manners is still not so pervasive as it needs high computational power to learn the network weights and depends on high management overhead. In contrast, the centralized manner the NNs learn multiple outputs and decision boundaries at once [29], which resolves several network challenges using the same model. For example. a sensor node localization problem is considered as application of NNs in WSNs. Node localization is performed by propagating angle and distance measurements of the received signals from anchor nodes [30] and such measurements involve time of arrival (TOA), received signal strength indicator (RSSI) and time difference of arrival (TDOA) as illustrated in Fig.1. Using supervised training, neural network estimates position of sensor node as vector quantity in 3D space. The algorithms based on neural networks are generally self-organizing map or Kohonen's maps and learning vector quantization (LVQ) which are detailed in [31]. In addition to estimation of functions, the important applications of neural networks is found in high-dimensional and complex data set (Big Data) which tunes and reduces dimension of data[32].

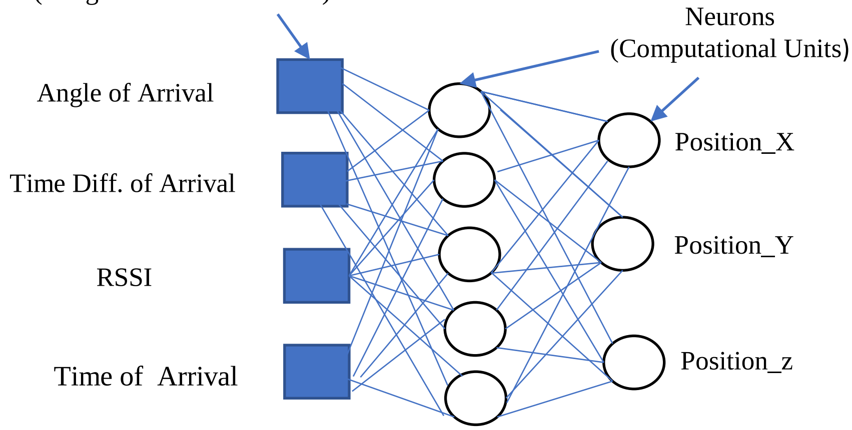

Fig.1. Position Estimation Using Supervised Learning

4) Support Vector Machines (SVMs)

This machine learning algorithm learns to classify data points by using labelled training samples [33]. For example, SVM approach is used to identify malicious behaviour of a node and that is done by investigating temporal and spatial correlations of data. In Fig.2 the working is shown the observation made are shown as points in feature space. The SVM forms partition in the space and these partitions are separated by as wide as possible margins and new observations are classed and placed in either side of the gaps they fall on. An SVM algorithm, which includes optimizing a quadratic function with linear constraints (that is, the problem of constructing a set of hyperplanes), provides an alternative method to the multi-layer neural network with nonconvex and unconstrained optimization problem [26]. Potential applications of SVM in WSNs are security (e.g., [20-21], [34-36] and localization e.g. [37-39]. The SVM theory is explained in [33] in detail.

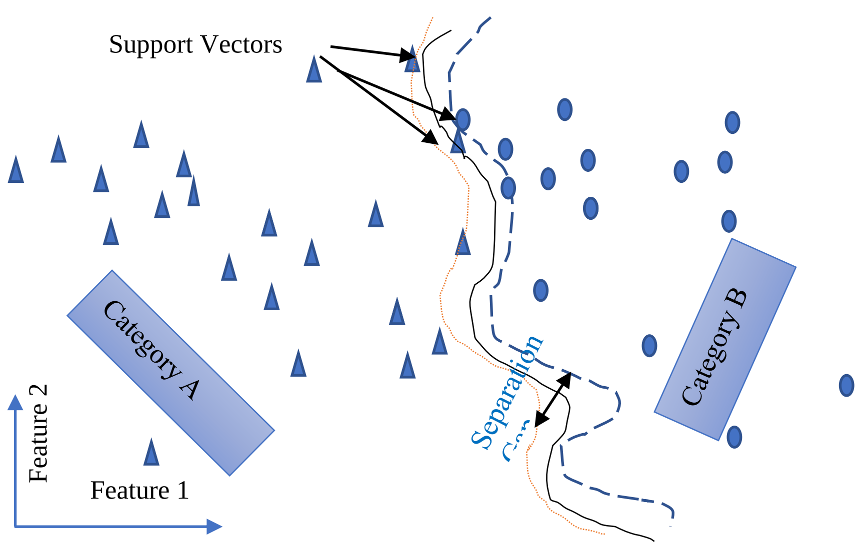

Fig.2 Non Linear Support Vector Machine

5) Bayesian Statistics

Bayesian inference needs a relatively small set of training samples [40] in contrast to machine learning algorithms. Bayesian methods uses probability distribution function to learn uncertain concepts (e.g., θ) without over-fitting efficiently. The algorithm uses the current knowledge i.e. collected data abbreviated as D to update prior beliefs into posterior beliefs $p(\theta|D) \propto p(\theta)\ p(D|\theta)$, where $p(\theta|D)$ is the posterior probability of the parameter θ given the observation D, and $p(D|\theta)$ is the likelihood of the observation D given the parameter θ. One application of Bayesian inference in WSNs is to assess event consistency (θ) using incomplete data sets (D) by investigating prior knowledge about the environment. But, such statistical knowledge requirement restricts the wide usage of Bayesian algorithms in field of WSNs. A Gaussian process regression (GPR) model [41] is also statistical learning algorithm related to above.

B. Unsupervised Learning

In unsupervised learning, there is no output vector i.e. it does not provide labels. Basically, this learning algorithm classifies the sample data set into different groups by recognizing similarity between them. Theme of learning algorithms is widely adopted in clustering and data aggregation problems as discussed in [42-48]. Followings are the major algorithms of unsupervised learning.

1) K-Means Clustering

The k-means algorithm [49] groups data into different classes known as clusters. The unsupervised learning algorithm is widely adopted in clustering of sensor node as its implementation is simple and has linear computational complexity. The steps needed to resolve such node clustering problem are (1) randomly selecting k nodes as the initial centroids for different clusters; (2) labelling of each node with the closest centroid using a distance function; (3) Re-computation of the centroids using the current node memberships and (4) stop the above process if the convergence condition is valid such as a threshold is defined for the sum of distances between nodes and their perspective centroids), otherwise go back to step (2).

2) Principal Component Analysis (PCA)

It is basically technique to compress data by reducing its dimension by extracting important information exhibited from collected data set and transform it into a new orthogonal variable called principal components [50]. As shown in Fig. 3, the principal components of data are in order such that the first component corresponds to the highest-variance direction of the data, and so on for the other components. By this way the least-variance data components can be discarded as they contain the information content of least importance. Finally, PCA reduces the amount of transmitted data among sensor nodes by finding a small set of uncorrelated linear combinations of original readings. Furthermore, this technique simplifies the problem by considering only few conditions in very large variable problems (i.e. tuning big data into tiny data representation) [51]. A thorough description of the PCA theory is discussed in [50].

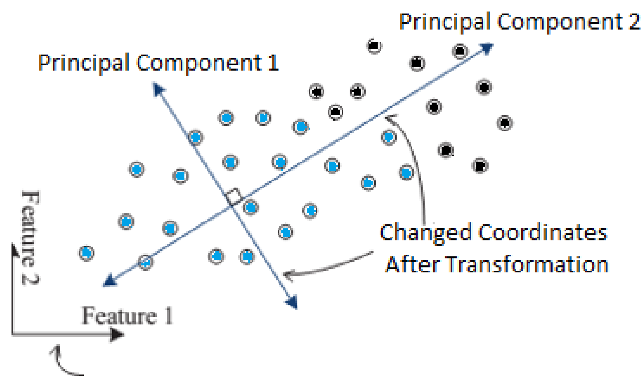

Fig.3 2-D Visualization of PCA Algorithm

C. Reinforcement Learning

Reinforcement learning enables a sensor node to learn its environment by interacting it. The agent learns to take the best actions that maximize its long-term benefits using its own experience. A well-known algorithm, Q-learning is a reinforcement learning technique is explained in [52]. As illustrated in Fig. 4, an agent updates its achieved benefits acquired due the action taken at a given state on a regular basis. The total benefits awarded known as the Q-value of performing an action (A_t) at a given state S_t is estimated as shown in equation (1). This algorithm can be easily implemented in a distributed architecture such as wireless sensor network where each node takes actions that are expected to maximize its long-term benefits. It is important to note that Q-learning has been extensively and efficiently used in WSN routing problem.

$$Q(S_{t+1}, A_{t+1}) = Q(S_t, A_t) + \alpha\ (\ b(S, A_t)\ - Q(S_t, A_t))$$

(1)

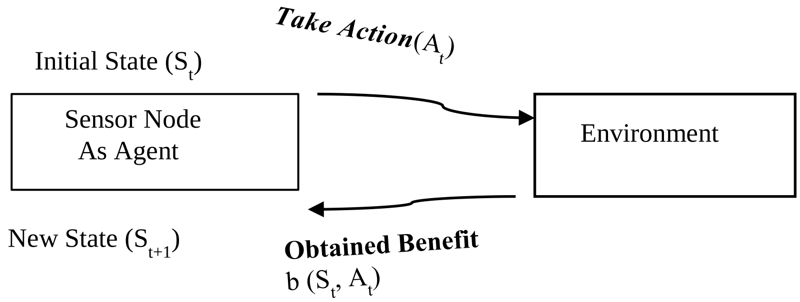

Fig.4. Q-Learning Method, A Visualization

III. Related Work

Some seminal localization techniques for wireless sensor network using machine learning are summarized as followed.

1) Bayesian Node Localization

Morelande et al. [8] has worked upon developing a localization scheme for sensor networks which utilizes a few anchor nodes. This works upon the enhancement of progressive correction [53] technique to predict samples from likelihoods to get closer to the posterior likelihood. This algorithm is efficiently applicable for localizing large networks i.e. comprised of a few thousands of sensor nodes. The novel idea of using the Bayesian algorithm to localize is appealing as it can handle incomplete data sets by investigating prior knowledge and probabilities.

2) Robust Location-Aware Activity Recognition

Lu and Fu [9] has tried to address the issue of sensor and activity localization in smart homes. These activities of interest are listening to the music, using mobile or phone-sets, opening or closing fridge or studying, etc. In such sensor applications, the developers need to comply with the environmental and human constraints both and assure of its easy operation. This proposed model is named as “Ambient Intelligence Compliant Object” (AICO) which facilitates the interaction of humans with the electric devices used in our homes in an efficient way such as automatic power supply management. Its main functioning uses multiple naive Bayes classifiers to estimate the current location of residents and proves its reliability by detecting any sensors malfunctioning. This method is a robust mechanism for localization, but dependent on applications and the developers must provide a set of supported activities additionally. Depending on the activities and the domain of interest, used learning features are selected and evaluated manually. To overcome the above problem in centralized system, it is recommended to investigate unsupervised machine learning algorithms for automatic feature extraction such as the deep learning methods [28] and the non-negative matrix factorization algorithm [54].

3) Localization Based on Neural Network

The localization techniques based on different types of neural networks are basically compared and discussed by Shareef et al. in [10]. This discussion has compared localization using multi-layer perceptron (MLP), recurrent neural networks (RNN) and radial basis function (RBF) and concludes that RBF neural network results with minimum localization error at the cost of high resource requirements. On contrary, the MLP results with the minimum consumption of computational and storage resources.

Similarly, Yun et al. [55] proposed two classes of algorithms for localization of sensor node using RSSI from anchor nodes. The first class uses the fuzzy logic system and genetic algorithm whereas the second class adopts the neural network to predict the location of sensor node using RSSI measurements from all anchor nodes as an input vector.

On similar pattern Chagas et al. [56] used neural networks for localization with RSSI as an input to the learning network. The main advantage of these Neural network based localization algorithms lies in its ability to provide position in the form of continuous-valued vectors. This is unlike statistical or Bayesian alternatives as it is a non-probabilistic method. This way it limits the precision of unknown node’s estimated positioning and thereby restricts the cost of localization errors.

4) Localization Using Support Vector Machine (SVM)

The SVM technique has been widely adopted for sensor node localization where attaching a self-positioning device to each sensor node is infeasible. On this way, Yang et al. [39] proposed a localization technique for mobile node by adopting SVM and connectivity information capabilities. In its initial stage, the proposed method discovers node movement pattern using their radio frequency oscillation such as RSSI metric. For movement detection, SVM will be executed to provide the new location. Similarly, in [39] Tran and Nguyen [38] worked upon localization techniques based on Support Vector Machines" (LSVM) to localize nodes in sensor applications.

5) Localization Using Support Vector Regression (SVR)

On The wide adoption of SVR learning recedes the performance of wireless sensor networks due to constrained resources and multi-dimensional data. This leads Kim et al. [37] to develop the idea of using lightweight implementation of SVR by partitioning the original regression problem into several 13 sub-problems. Basically, the algorithm progresses by dividing the whole network into a set of sub-networks, so that small number of data is to be processed by each regression algorithm (i.e., SVR's sub-predictors). Thereafter, the learned hypothesis models of the sub-predictors are joined together using a customized ensemble combination technique. This way, in addition to its low computational requirements and robustness against noisy data, this solution converges to the preferred solution. As given an appropriate training data, LSVM uses multiple decision metrics like connectivity information and indicators to achieve its design goals. Although, LSVM provides distributed localization in efficient and fast way, still its performance is sensitive to outliers in training samples.

6) Localization Based on Decision Tree

Merhi et al. [57] proposed an acoustic target localization technique based on decision tree learning for wireless sensor networks. The positioning of targets are estimated using the time difference of arrival (TDOA) of signals forming a spatial correlation decision tree and furthers the design of "Event Based MAC" (EB-MAC) protocol which enables event-based localization and targeting in acoustic wireless sensor network. The EB-MAC was implemented using a MicaZ board supporting ZigBee 802.15.4 specifications for personal area networks. The propagation limitation of the GPS signal through water do not make the localization of sensor applications inside water feasible [58]. Erdal et al. [59] has proposed solution for submarine detection in underwater surveillance systems which locates randomly deployed node in space using position coordinates of anchor nodes. In this each monitoring unit has a sensor node fixed with a cable to a surface buoy and data is collected using the buoys, then after they are transmitted to the central control unit. A decision tree classifier is basically used to detect any submarines in the monitored sites.

7) Placements of Sensors Using Gaussian Processes

An optimized solution for the placement of sensors in applications requiring spatially correlated data i.e. temperature monitoring systems is provided by Krause et al. in [60]. One of the important development is of a lazy learning scheme that is based on Gaussian process model to detect a phenomenon. Lazy learning algorithms basically stores training samples and delay the major processing until a classification request is received. Moreover, this aims to provide optimal locations for sensors even in node failures and model ambiguity.

8) Localization Using Spatial Gaussian Process Regression Method

A distributed protocol for collective node motion is provided by Gu and Hu in [61]. This basically uses distributed Gaussian process regression (DGPR) to predict optimal solutions for positioning of mobile nodes. In traditional algorithms of Gaussian process regression (GPR), computational complexity is of order O(N3), where N is the size of samples instead this solution uses a sparse Gaussian process regression algorithm to reduce its computational complexity. In this approach, each node will execute the regression algorithm independent to others using only spatiotemporal information from local neighbours.

9) Localization Using Self-Organizing Map

Paladina et al. [62] proposed solutions for the positioning of WSNs consisting of thousands of nodes using Self Organising MAP (SOM). The proposed algorithm is executed in each node with a simple SOM algorithm that consists of a 3x3 input layer connected to the 2 neurons of the output layer. Particularly, the input layer is formulated using the spatial coordinates of 8 anchor nodes neighbouring the unknown node. The output layer is used to represent the unknown node's spatial coordinates in a 2D space after sufficient training. The basic cons of this method is that the deployment of nodes should be equally spaced throughout the monitored area.

Giorgetti et al. [63] proposed a localization algorithm using only connectivity information and the SOM algorithm unlike the traditional algorithms requiring absolute locations of anchor nodes to localize the unknown nodes. This algorithm is highly suits to networks with constrained resources as not requiring a GPS-enabled device. Since this is a centrally executed algorithm, each node conveys the information of its neighbours to the core unit to produce the adjacency matrix and thus location of the node.

In same way, Hu and Lee [64] provides node localization in WSNs without needing anchor nodes. This algorithm operates efficiently for any number of nodes and is based on preparation of SOM. The contribution of [64] over [63] is that the proposed algorithm distributes the computation tasks to all nodes in the network, which eliminates the needs for a central unit and minimizes the transmission overhead of the algorithm.

10) Dynamic Routing Based on Reinforcement Learning

Li et al. [65] developed a reinforcement learning-based localization method for WSNs, called “Dynamic Path determination of Mobile Beacons” (DPMB), suitable for real-time management of the mobile beacons. The mobile beacon (MB), which is aware of the physical location during its movement, will be used to determine the positions of large number of sensor nodes.

In brief, the states of the Q-learning algorithm are used to represent the different positions of the MB, and the algorithm target is to cover all the sensors in the monitored area (i.e., all the sensors should hear a location update message from the MB at some stages). The entire operation will be run in the mobile beacon, and hence, this will save the resources of the unknown nodes. However, as a centralized method, the entire system will fail in the event of mobile beacon malfunctions.

Proposed Methodologies for localization	**Underlying Algorithm(s) Using Machine Learning**	**Centralized/ Distributed**	**Computational Complexity of Algorithms**	**Anchor/ No Anchor**
Location-Aware Activity Recognition [9]	Bayesian	Centralized	Moderate	Anchor
Bayesian Lode Localization [8]		Centralized	Moderate	Anchor
Localization based on NNs [10]	Neural Networks	Centralized	High	Anchor
Soft Localization [55]		Distributed	Moderate	Anchor
Localization Based on NNs [56]		Distributed	High	Anchor
Area Localization [39]	Support Vector Regression	Distributed	Moderate	Anchor
Localization using SVR [37]		Distributed	Moderate	Anchor
Localization using SVM [38]	Support Vector Machine	Distributed	Moderate	Anchor
Target Classification and Information Fusion [58]	Decision Tree-Based Localization	Distributed	Low	Anchor
Underwater Surveillance System [59]		Centralized	Moderate	Anchor
Sensor Placements [60]	Gaussian Processes	Distributed	Low	Anchor
Spatial Gaussian Process Regression [61]	Gaussian process regression	Distributed	Moderate	Anchor
Localization in 2D Space [62]	Self-Organizing Map	Distributed	Moderate	Anchor
Localization Using SOM [63]		Distributed	Low	No Anchor
Distributed Localization [64]		Distributed	Moderate	No Anchor
Path Determination [65]	Reinforcement Learning	Centralized	Low	Anchor

IV. Conclusion and Future Direction

Wireless sensor networks are different from traditional network in various aspects, thereby needs algorithms addressing specific challenges and limitations posed by WSN. Therefore, wireless sensor networks necessitate innovative solutions to save energy and performance in real-time routing, localization, data aggregation, node clustering, fault detection and data integrity. Machine learning provides techniques and methods to improve the performance of wireless sensor network to work with dynamic surrounding environment. In this paper, an extensive literature review over localization of sensor network adopting machine learning algorithms is presented that considers the limited resources of the network as well as the varying learning themes and patterns according to the problem considered. Moreover, various issues are still open for future research such as developing lightweight and distributed message passing techniques, hierarchical clustering patterns, online learning algorithms and adopting machine learning is also in resource management problem of wireless sensor networks.

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