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A Survey on Localization in Wireless Sensor Networks using Stochastic Pattern Recognition Algorithms

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***Abstract*— Utilizing localization systems is an important issue for many applications in wireless sensor networks (WSN). In some applications, sensors may be deployed in areas where are not accessible by human and the location of sensors is unknown. Using global positioning system (GPS) in each sensor is expensive and power consuming. Therefore, efficient localization algorithms should be performed to localize the sensors in the network. Many techniques are introduced for localization in WSNs in which range based techniques are well studied in the literature. In this paper, we study stochastic pattern recognition (SPR) algorithms used for localization in WSNs. We categorize the proposed methods and compare their usage and properties.**

***Index Terms*— wireless sensor networks; localization; stochastic pattern recognition; k-nearest neighbor; support vector machine; hidden Markov model.**

I. Introduction

Recent developments in electronics and telecommunications have led to significant increase in usage of inexpensive and low power sensors. These sensors are physically small and are capable to communicate with each other in short distances. Each sensor collects information from its surrounding environment and process it according to the application.

WSNs consist of several nodes deployed in an area and their location is not necessarily known. We can use these nodes in places where are not accessible by human. Feasibility of data communication between nodes is another advantage of these networks. Nodes can communicate with other nodes and share their information. Wireless sensors are used in many applications such as security, environmental monitoring, industry, monitoring of agricultural land and so on.

In many applications of WSNs, information is applicable and meaningful only when the locations of sensors are known. It is usually not reasonable to use global navigation systems such as GPS in all sensors due to its cost and power consumption. Therefore, other methods are used to estimate the location of sensors. The procedure of estimating the location of sensors in the network is called localization. Localization has attracted many researchers in the last decade. Many algorithms are used for localization such as range based techniques and range free techniques. One category of localization algorithms are based on stochastic pattern recognition (SPR). Pattern recognition is a about categorizing and information clustering according to the specific properties. This technique is used in several applications and many fields. In this paper, we study the SPR based localization algorithms and categorize them according to their applied methods.

The rest of this paper is organized as follows: In section II we introduce range based methods used for localization. In section III, SPR algorithms are introduced and SPR based localization algorithms are presented in section IV. Finally, we conclude the paper in section V.

II. Location Estimation in WSNs

There are several methods that are used to collect the range information, which is further processed to estimate the location of sensors in a network. We introduce some of them in the rest of this section.

A. *Received Signal Strength (RSS)*

In this method there is a transmitter with known power that broadcast a signal for all sensors in the network. Each sensor node estimates its distance toward the transmitter based on the received power. The RSS based distance estimation is inaccurate, and channel and path loss parameters should be known and considered to improve the accuracy of estimation [1]. For localization using RSS, there are two methods; geometric methods and finger-print one.

B. *Time of Arrival (TOA)*

To localize a sensor node using TOA, the propagation time of signal between reference point and sensor nodes is measured and considering the speed of signal propagation (near to speed of light), the distance between reference point

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and sensor node is calculated. Given this distance, the localization is performed. This method requires time and frequency synchronization of reference node and sensor nodes.

C. Time Difference of Arrival (TDOA)

In this method, the difference of signal propagation time between nodes and reference point is measured. TDOA method do not need the synchronization of transmitter and receiver. However, this method is more complex than TOA and is used in GPS [2-3].

D. Direction of Arrival (DOA)

In this method, sensor nodes measure the direction to of signal and use that angle to localize the target. In the networks which use this method, there are usually an array of antennas to estimate the direction of received signal. The accuracy of estimated direction depends on antenna configuration and line of sight signals. Additionally, array antenna increases the complexity of system [2-3].

III. SPR ALGORITHMS

SPR is a branch of machine learning which categorizes data to make decision. Pattern recognition algorithms classify data using prior information. Patterns which are classified by this methods are a group of measurements or observations allocated to a point in space by prior data. In the rest of this section, we express some SPR methods.

A. Decision Tree

Decision tree is one of the nonparametric classification methods. Diverse indexes and variety of methods exist to determine decision tree. One of this algorithms is CART [4] introduced by Breiman in 1984 which implements a decision tree with binary decisions. In this model, pruning of tree is performed according to a cost function. One of the problems of this model appears in qualitative variables with more than two levels [5].

B. Multidimensional Scaling

This method is typically used in visual information. In multidimensional scaling, a distance matrix formed for information and this method tries to convert information to the multidimensional environment without changing in distances. Typically, multidimensional scaling mentioned as an optimization problem.

C. K-Nearest Neighbor (KNN)

This method is one of the nonparametric algorithms to calculate distribution function from information. In this method, when new element entered to the space, finds elements which have minimum distance to itself. This distance means that the new element and its neighbors have the same properties and are classified in the same class. This method is one of the most popular methods for information classification.

D. Neural Networks

Neural networks are one of the most popular and most practical methods to model complex problems. This method is used for both classification problems in which the output is a class and regression problems in which the output is a number.

E. Support Vector Machine (SVM)

This method is one of the classification algorithms considered as kernel based algorithms in machine learning. SVM was introduced by Vapnik in 1992 and is based on stochastic learning. This method assumes that levels are linearly separable and if this assumption cannot hold, it maps data to the new environment to separate them linearly.

F. Hidden Markov Model (HMM)

HMM is a stochastic model. In this model, modeled system is considered as a Markov process with hidden states. In typical Markov model, states are observable and the parameter is just the probability of transfer between states, however, in HMM some states are not observable straightly and each state has a distributed probability on the output symbols.

IV. LOCALIZATION IN WSNS USING SPR ALGORITHMS

In several applications, awareness of sensor's location is required to proper usage of network [13]. In this section, we review some works on localization in WSNs using SPR algorithms. These papers are categorized in Figure 1.

In [6] two methods of localization i.e. SVM and CART are introduced. In this paper, RSS from a reference point is considered as input and location information as output of model. In [6] two mentioned methods are implemented in 100x100 [m^2] area. Authors in [6] train both of methods with same information, then change the problem of localization to the problem of classification. As indicated in [6], localization using CART needs less time but SVM has less error in comparison with CART. Therefore, there is a tradeoff between time and accuracy.

In [7], the location estimation based on time of flight is introduced. In this paper, in order to localize target based on RF, a classical multidimensional scaling (C-MDS) method is introduced to calculate the estimated location by Euclidean kernel. Results of [7] show that iterative C-MDS method could be performed in small scale WSNs and this method is compatible to the network when sensor nodes are not connected to the RF nodes.

In [8], an application of WSNs for indoor localization using IEEE 802.15.4 is introduced. The proposed algorithm

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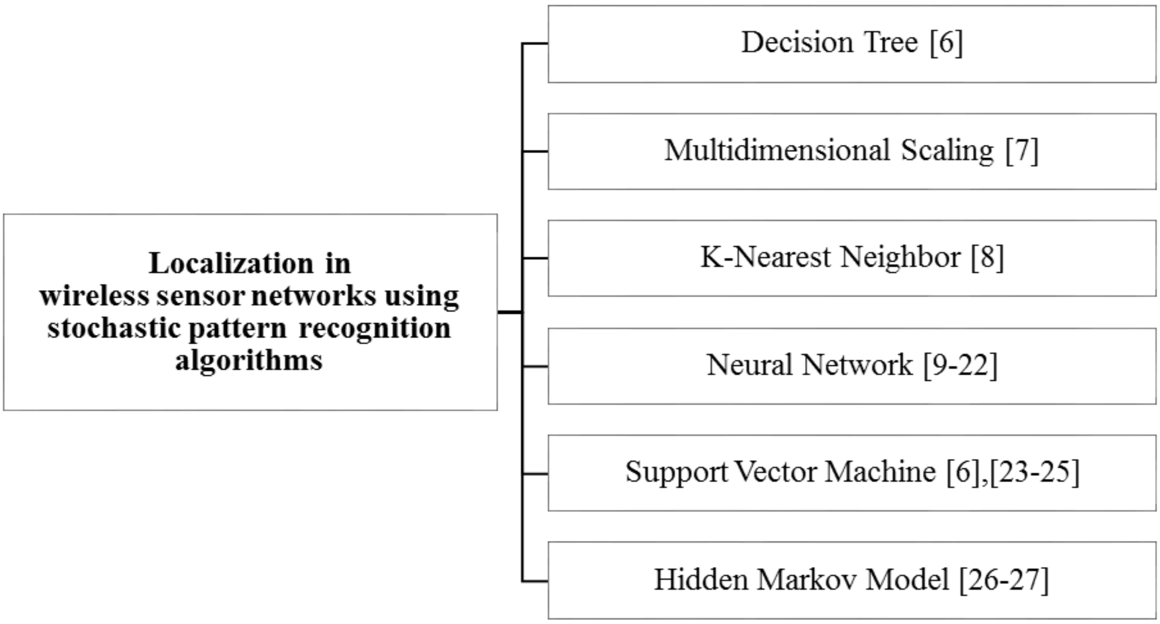

Fig. 1. SPR algorithms used in localization for wireless sensor networks

in [8] applies k-means clustering and genetic algorithm as a motor for offline information preparation and use combination of this two methods to localize the target. This leads to increase the accuracy and decrease computational cost for indoor fingerprint localization [8]. As mentioned in [8], results are obtained in indoor using Zigbee and compared with KNN and WDF. In [10] TDOA and neural network are used to localize target in WSNs. At first, TDOA is used to estimate distance between target and anchor nodes. Then this distances is used to train neural network. Results in [10] show that the localization error in this network decreases when the density of nodes are increases.

Authors in [11] introduced a new method to localize target in WSNs. This method called iterative CCA-MAP (ICCA-MAP) and is based on CCA-MAP which is mapped to a nonlinear method. This nonlinear method is useful for fix nodes in WSNs. The error of both algorithms are almost the same but ICCA-MAP requires less computational time. Therefore, this method could be used for cases which need real time process. Authors in [13] introduced a localization method for ad-hoc wireless networks. This method is based on neural networks and decreases energy consumption. Another advantage of this method is its decreased computational complexity. Meanwhile, the sensitivity of this method to noise is less than other methods [13].

In [14] genetic algorithm is applied to neural networks to localize sensor nodes. In this paper, RSS used as the input of neural network. After calculation of outputs of neural network, genetic algorithm is used to decrease the error. Authors in [20] use KNN to estimate the location of target node. In proposed method, neighbors are categorized to two groups, single neighbor node and successive neighbor node. This method decreases computational time considerably. Also this method could be used for classification and clustering of sensor nodes beside the localization [20].

In [23] a 3D localization method introduced based on SVM for WSNs. In this paper, at first each target node estimates its distance to the anchor nodes and collect them in a vector. This vectors are used for training of SVM algorithm. After classification of target node, target placed in 3D area and the middle point of this cube is the location of target. Results show that proposed algorithm of [23] is insensitive to number of anchor nodes. Authors in [25] uses hierarchical SVM to localize target node.

In proposed method of [26], nodes that do not have GPS localize themselves using the information of some nodes which use GPS. In [26] localization is performed by using HMM. Results show that using semi-Markov smooth model leads to increase the accuracy of HMM. This method is not sensitive to the type of sensors. Authors in [27] proposed method to localize nodes which do not use GPS by the information of some nodes which use GPS. In [27], nodes measure RSS to estimate their distance from other nodes. Then nodes use this distance to estimate target location using HMM.

V. CONCLUSION

In this paper we reviewed wireless sensor localization which use SPR algorithms. At first we introduced the methods which are used to collect information from environment and then expressed SPR algorithms used in localization procedure. Then, we reviewed target localization in WSN using SPR algorithms. We may conclude that localization using decision tree requires less time than SVM, however, SVM has less localization error. Also we may conclude that iterative C-MDS has good performance in small scale networks. Meanwhile, joint usage of k-means clustering and genetic algorithm increases the accuracy and decreases the computational cost of indoor fingerprint localization. Results show that ICCA-MAP method requires

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less time than other methods and can be used in real time projects. Additionally, we can conclude that HMM is insensitive to the type of sensor nodes.

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