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DECISION TREE BASED LOCALIZATION IN WIRELESS SENSOR NETWORKS

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ABSTRACT

Localization in Wireless Sensor Network (WSN) plays a vital role in applications such as military, medical, healthcare, civil and environmental applications etc. Since all the sensor nodes in wireless sensor network are battery powered it is highly required to effectively utilize the sensor nodes in such a way that the lifetime of WSN is higher. Due to the limited availability of battery power in sensor nodes, energy consumption, computation speedup and memory consumption of localization algorithms are to be considered. In this paper a novel decision tree based approach (DTBL) for locating the nodes in WSN is discussed. The proposed approach is energy efficient in nature and high level of accuracy is obtained when compared with other localization techniques.

Keywords: WSN, Sensor, Lifetime, Decision Tree, Energy.

INTRODUCTION

A wireless sensor network is a group of specialized transducers with a communications infrastructure for monitoring and recording conditions at diverse locations. Commonly monitored parameters are temperature, humidity, pressure, wind direction and speed, illumination intensity, vibration intensity, sound intensity, power-line voltage, chemical concentrations, pollutant levels and vital body functions. A sensor network consists of multiple detection stations called sensor nodes, each of which is small, lightweight and portable. Every sensor node is equipped with a transducer, microcomputer, transceiver and power source. The transducer generates electrical signals based on sensed physical effects and phenomena. The microcomputer processes and stores the sensor output. The transceiver receives commands from a central computer and transmits data to that computer. The power for each sensor node is derived from a battery.

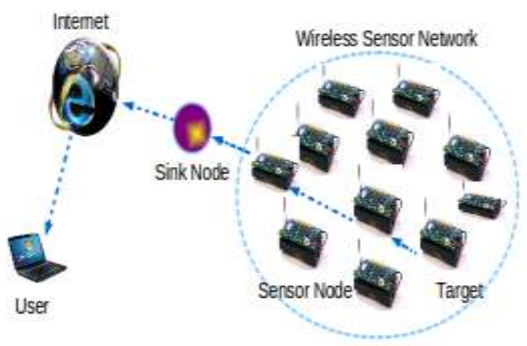

Fig 1: Illustration of Wireless Sensor Networks

Wireless Sensor Networks are:

- Self-configuration, Self-healing, Self-optimization, and Self-protection capabilities
- Short-range broadcast communication and multi-hop routing
- Dense deployment and cooperative effort of sensor nodes
- Frequently changing topology due to fading and node failures
- Severe limitations in energy capacity, computing power, memory, and transmit power.

Localization

Localization determines the physical coordinates of a group of sensor nodes. These coordinates can be global, meaning they are aligned with some externally meaningful system like GPS, or relative, meaning that they are an arbitrary "rigid transformation" (rotation, reflection, translation) away from the global coordinate system. Beacon nodes (also called anchor nodes) are a necessary prerequisite to localize a network in a global coordinate system. Beacon nodes are simply ordinary sensor nodes that know their global coordinates a priori. This knowledge could be hard coded, or acquired through some additional hardware like a GPS receiver. At a minimum, three non-collinear beacon nodes are required to define a global coordinate system in two dimensions. If three dimensional coordinates are required, then at least four non-coplanar beacons must be present.

Localization accuracy improves if beacons are placed in a convex hull around the network. By planning beacon layout in the network real improvements in localization can be obtained. The presence of several prelocalized nodes can greatly simplify the task of assigning coordinates to ordinary nodes. But the disadvantage is GPS receivers are expensive. GPS receivers also consume significant battery power, which can be a problem for power-constrained sensor nodes.

Localization algorithms in wireless sensor network contain three main phases:

- **Distance estimation** involves measurement techniques to estimate the relative distance between the nodes.
- **Position computation** consists of algorithms to calculate the coordinates of the unknown node with respect to the known anchor nodes or other neighboring nodes.
- **Localization algorithm** determines how the information concerning distances and positions, is manipulated in order to allow most or all of the nodes of a WSN to estimate their position.

There are four common methods used in distance estimation technique. They are:

- Angle of Arrival (AoA) - evaluates the relative angles between received radio signals.
- Time of Arrival (ToA) - estimates distances between two nodes using time based measures.
- Time Difference of Arrival (TDoA) - determines the distance between a mobile station and nearby synchronized base station.
- Received Signal Strength Indicator (RSSI) - translates signal strength into distance.

Position computation includes the following techniques:

- Lateration - based on the precise measurements to three non collinear anchors. Lateration with more than three anchors called multilateration.
- Angulation (or triangulation) - based on information about angles instead of distance.

Localization algorithms can be classified into several categories such as:

- Centralized Vs Distributed
- Anchor-free Vs Anchor-based
- Range-free Vs Range-based
- Mobile Vs Stationary involves

The following table shows the techniques used by Range-Free and Range-Based methods.

Table 1. Localization Techniques

Method	Techniques used
Range-Free	Local Techniques Hop-Counting Techniques
Range-Based	Received Signal Strength Indicator (RSSI) Time of Arrival (ToA) Time Difference of Arrival (TDoA) Angle of Arrival (AoA)

Classification

Classification is a form of data analysis that extracts models describing important data classes. Such models, called classifiers, predict categorical (discrete, unordered) class labels. Data classification is a two-step process, consisting of a learning step (where a classification model is constructed) and a classification step (where the model is used to predict class labels for given data). In the first step, a classifier is built describing a predetermined set of data classes or concepts.

This is the learning step (or training phase), where a classification algorithm builds the classifier by analyzing or "learning from" a training set made up of database tuples and their associated class labels. A tuple, X, is represented by n-dimensional attribute vector, $X = (x_1, x_2, \dots, x_n)$, depicting n measurements made on the tuple from n database attributes, respectively, $A_1, A_2, \dots, A_n$. Each tuple is assumed to belong to a predefined class as determined by another database attribute called the class label attribute.

Because the class label of each training tuple is provided, this step is also known as supervised learning (i.e., the learning of the classifier is "supervised" in that it is told to which class each training tuple belongs). A test set is used, made up of test tuples and their associated class labels. They are independent of the training tuples, meaning that they were not used to construct the classifier. A decision tree is a flowchart-like tree structure, where each internal node (nonleaf node) denotes a test on an attribute, each branch represents an outcome of the test, and each leaf node (or terminal node) holds a class label. The topmost node in a tree is the root node. IF-THEN rules are extracted from decision tree which form classification rules for set of training data. An IF-THEN rule is an expression of the form

IF *condition* THEN *conclusion*

DV-HOP ALGORITHM

Initially, each beacon node broadcasts a beacon to be flooded throughout the network containing the beacons location with a hop-count value initialized to one. Each receiving node maintains the minimum hop-count value per beacon of all beacons it receives. Beacons with higher hop-count values to a particular anchor are defined as stale information and will be ignored. Then those not stale beacons are flooded outward with hop-count values incremented at every intermediate hop. Through this mechanism, all nodes in the network get the minimal hop count to every beacon node.

Then, once a beacon gets hop-count value to other beacons, it estimates an average size for one hop, which is then flooded to the entire network. After receiving hop-size, blindfolded nodes multiply the hop-size by the hop-count value to derive the physical distance to the beacon.

Fig 2 explains DV-Hop algorithm. In this figure A, B, C are beacons. Actual distance between beacons is also mentioned. The beacons calculate the average distance of each hop according to Fig 3. The average distance can be used to correct the position. The node N is getting its direction from B. The distance can be obtained as specified in Fig 4.

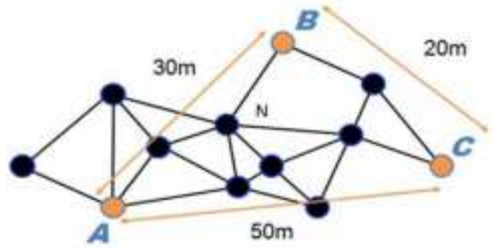

Fig 2: Network containing 3 beacons

- A: (30+50)/(3+4) = 11.4m
- B: (30+20)/(3+2) = 10m
- C: (50+20)/(4+2) = 11.7m

Fig 3: Average distance calculation

$$N_A = 10 \times 2 = 20m, N_B = 10 \times 1 = 10m, N_C = 10 \times 2 = 20m$$

Fig 4: Distance calculation for node N

RELATED WORK

Carlos Moreno-Escobar, Ricardo Marcel´ın-Jim´enez, Enrique Rodr´ıguez-Colina and Michael Pascoe-Chalke presented a method [3] to reduce the signaling overhead due to a distributed localization procedure. Each leader solves locally a particular instance of the Multi Dimensional Scaling (MDS) problem. Finally, a minimum set of beacons is selected on each cluster. This method significantly reduced the number of messages exchanged, which is an important operation condition for wireless sensor networks.

Based on decision tree learning, Merhi *et al.* [2] developed an acoustic target localization method for WSNs. Exact locations of targets are determined using the time difference of arrival (TDOA) metric in a spatial correlation decision tree. Also, this work proposed the design of "Event Based MAC" (EB-MAC) protocol that enables event-based localization and targeting in acoustic WSNs. The proposed framework was implemented using a MicaZ board that supports ZigBee 802.15.4 specifications for personal area networks.

Using the GPS functionality to support localization in underwater wireless sensor network's applications may not be feasible due to the propagation limitation of the GPS signal through water [5]. Erdal *et al.* [3] developed a system for submarine detection in underwater surveillance systems, so that a randomly deployed node finds its location in the 3D space based on beacon node coordinates. Each monitoring unit consists of a sensor that is fixed with a cable to a surface buoy. Data is collected using the buoys, where they are transmitted to the central processing unit. At the central unit, a decision tree classifier is used to recognize any submarines in the monitored.

In [5], the authors describe a surveillance network that can detect moving targets. The system uses Mica2 motes [7] equipped with a magnetometer (Honeywell HMC1002 [6]), an acoustic sensor and, on some nodes, a motion sensor. The motion sensor is an Advantaca MIR (micropower impulse radar) sensor which transmits microwave signals and detects motion by capturing distortion the reflected signal. The network reports a target as a walking person or a vehicle. Therefore, it has a preliminary classification capability. However, there is very limited signal processing in it. As a result, the classification is limited in both functionality and performance.

Brooks et. al. [8] introduced a collaborative signal processing framework for sensor networks using location-aware routing and collaborative signal processing. Their study provides many insights into the distributed collaborative classification in WSNs. Nevertheless, the CSP framework involves non-trivial training and computation overhead, which our system cannot afford. Also, the system implementation and evaluation of the CSP framework employ nodes with higher power than the energy-and-cost-effective WSN nodes our system is targeting.

PROPOSED APPROACH

In this section, we present a novel decision tree based method for efficient position estimation in wireless sensor network. This technique is useful in situations when approximate position estimation is sufficient for decision making operations. Residual energy is considered for selecting the beacon nodes in the network.

The proposed method follows the steps given below for efficient localization in WSNs.

1. Initialize the Beacon node S.
2. Beacon node S receives signals flooded from all the other nodes in the network. Broadcast signals from S to all the other nodes in the network.
3. Calculate payload (W_i) of nodes by considering their chemical proportion values and residual energy.
4. Consider the nodes having payload values higher than Threshold value.
5. Construct a decision tree using these nodes by connecting with their neighbors.
6. Trace the path from the root node to each leaf node in the tree.
7. Localize the nodes by converting decision tree into n IF-THEN classification rules.

SIMULATION RESULT

We have validated our DTBL method using simulation. We consider energy consumption, location coverage, accuracy as measurement factors.

The experiment region is a square area with the fixed size of 100 X 100 m^2 and the nodes were randomly placed. We deploy 100 sensor nodes in a two dimensional space. The simulation results are presented in the following figures.

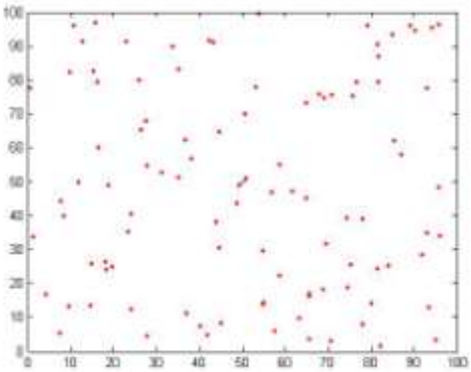

Fig 5: Random distribution of nodes

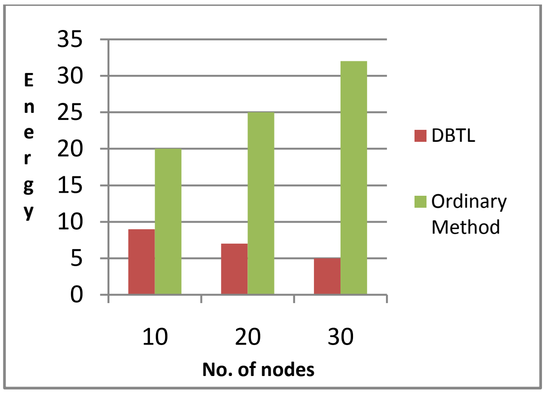

Fig 6: Energy consumption at nodes

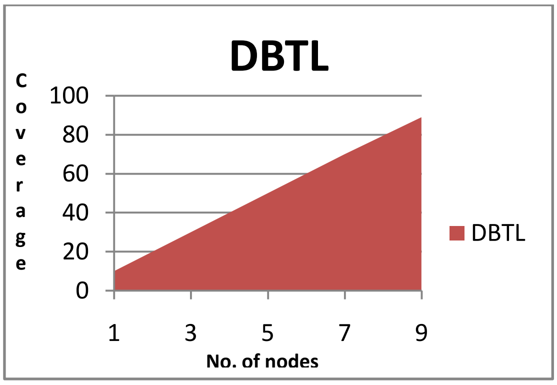

Fig 7: Location coverage of nodes

CONCLUSION

In this paper, we present a new decision tree based method DTBL for nodes localization in WSN. In our approach, network is represented as a tree structure and classification rules are formed using the decision tree. These rules are useful for finding the position of nodes in the network.

The results from our experiments, show better results than ordinary methods used for node localization. Our algorithm estimates the nodes location with greater accuracy with less energy consumption. Our algorithm has less energy consumption if compared with ordinary localization method.

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