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A Novel Cluster based Scheme for Node Positioning in Indoor Environment

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ABSTRACT--- Location estimation in Wireless Sensor Network (WSN) is mandatory to achieve high network efficiency. Identifying the positions of sensors is an uphill task as monitoring nodes are involved in estimation and localization. Clustered Positioning for Indoor Environment (CPIE) is proposed for estimating the position of the sensors using a Cluster Head (CH) based mechanism. The CH estimates the number of neighbor nodes in each floor of the indoor environment. It sends the requests to the cluster members and the positions are estimated based on the Received Signal Strength Indicators (RSSIs) from the members of the cluster. The performance of the proposed scheme is analyzed for both stable and mobile conditions by varying the number of floors. Experimental results show that the propounded scheme offers better network efficiency and reduces delay and localization error.

Keywords: Indoor positioning, Wireless Sensor Network (WSN), Localization, Cluster, RSSI

I. INTRODUCTION

Wireless Sensor Network (WSN) is a network of sensor nodes that communicate through wireless medium. They are employed in different applications like object tracking, monitoring physical phenomena like temperature humidity, patient health care and traffic. The main task of a sensor node is to collect information and transfer it to the Base Station (BS).

Identification of sensor positions in the Wireless Sensor Network (WSN) is the most important factor for achieving better performance. Among the many different challenges faced by the WSN, localization of sensor nodes is one of the main challenges. Position of the sensors can be estimated based on the distance, Global Positioning System (GPS) signals, and Received Signal Strength Indicator (RSSI), global navigation satellite system and trilateration techniques.

Due to some environmental features and poor availability, GPS devices cannot be used in a large WSN. In particular, location is estimated through communication between the localized node and the un-localized node. Trilateration techniques measure the distance between a node and a number of anchor points with known location. Triangulation makes use of geometric properties of triangles to estimate location. It needs two angles with the distance between nodes for location measurement. RSS based localization gives the relationship between the distance and the measured RSS value from the nodes which decays with distance. All these techniques are used in localizing mobile sensor nodes in the WSN. Efficient node localization improves network performance. Generally, fingerprint based solutions based on RSSI are employed in WSNs to track the target node. Hence, localization and positioning of sensors, and high energy consumption are the main challenges faced in a WSN. If the sensors are placed at suitable locations, data transmission can would involve lesser failure and drop rates.

II. RELATED WORK

Priyantha et al (2000) have presented Cricket, a location-support system for in-building, mobile, location-dependent applications that ensures user privacy, decentralized administration, network heterogeneity and low cost using off-the-shelf components.

Wang et al (2003) have designed an indoor wireless positioning system that involves the signal strength of Access Points (APs) in WLANs to determine the position of the mobile user.

Mandal et al (2005) have propounded Beep, an indoor location system that senses audible sound based on standard 3D multi-literation algorithms. They have presented the benefits of the proposed system over other systems making use of ultrasound and infrared signals without involving any special software.

Liu et al (2007), in their survey have compared the existing wireless indoor positioning solutions based on the parameters namely, complexity, accuracy, scalability, robustness, cost and precision.

Gu et al (2009) have presented a survey of many available (both research oriented and commercial solutions) indoor positioning systems and evaluated on various criteria viz. cost, robustness, commercial availability, complexity etc. and the trade-offs from the users' perspective. Au (2010) has proposed the compact RSS based real-time indoor positioning and tracking system using compressive sensing theory and evaluated it using experiments. Saab & Nakad (2011) have proposed a positioning system using Kalman filter that takes inputs from the backscattered signal power propagated from nearby RFID tags and a tag-path position database. Dawes & Chin (2011) have discussed the limitations of Received Signal Strength Indication Fingerprinting (RSSIF) in indoor localization by comparing various RSSIF based methods.

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They have evaluated the efficiency and accuracy of these methods on a common test-bed. They have also suggested improvements and modifications particularly targeting the impact on dense and transient access points and outlined the shortcoming in using Bayesian algorithm in case of uncontrolled environments.

Kim et al (2012) have propounded an autonomous and collaborative RSS fingerprint collection and localization system that overcomes the costly and time-consuming offline training phase. They have carried out experiments which show that reasonable location accuracy is obtained with automatic fingerprinting in indoor environments.

Das et al (2012) have discussed about open research issues related to the effective use of Wi-fi positioning system.

Feng et al (2012) have proposed an accurate RSS-based indoor positioning system using the theory of compressive sensing and implemented the proposed system on a Wi-Fi-integrated mobile device. They have evaluated the performance that demonstrates substantial improvement on localization accuracy.

Pratama et al (2012) have developed a sensor-based positioning system that can be applied generally to all individuals taking into consideration the variation of walking patterns of each individual.

Au et al (2013) have proposed an indoor tracking and navigation system based on RSS in Wireless Local Area Network (WLAN). It outperforms the widely used traditional positioning and tracking systems and reduces the Mean Position Error (MPE).

Mo et al (2014) have come up with a positioning system based on Spatial Division Clustering (SDC) for networks where physical distance is a constraint. They involve Genetic Algorithm (GA) and Support Vector Machine (SVM) techniques to improve positioning accuracy.

Yang et al (2015) have discussed about smart phone based indoor positioning systems for WSNs to localize the mobile node.

Arfwedson & Berglund (2015) have created an Android application with Graphical User Interface (GUI) that makes use of existing indoor positioning system for the smartphone.

Mo et al (2015) have proposed dimension reduction method which is based on the fingerprinting system for Wireless-Fidelity (Wi-Fi).

Maddio et al (2015) have proposed distributed indoor positioning system model WSNs with independent mobile nodes. Kim et al (2015) have designed an image based localization technique to localize the senor nodes in WSNs.

Caso et al (2015) have compared the metrics used for flat W-KNN and two step W-KNN algorithms. They have proposed a novel mixed approach that makes use of different metrics across the steps of the algorithms and suggest combination of different metrics in improving the positioning accuracy that preserves efficiency.

Wang et al (2016) have proposed deep learning finger based indoor positioning system that uses the Channel State Information (CSI) for localization in WSNs.

Potgantwar et al (2016) have designed RFID based indoor environment to improve the gain of RSS, stability and robustness.

Kuo et al (2016) have discussed about clustering based positioning scheme for sensor networks with indoor environments involving one and multi-floors.

Gharghan et al (2016) have propounded hybrid Particle Swarm Optimization-Artificial Neural Network (PSO-ANN). This technique is used to estimate the distance between the mobile node and the anchor node. To estimate the distance, this technique uses the Log Normal Shadowing Model (LNSM) and Feed Forward Neural Network (FFNN). LNSM uses the RSS of mobile nodes, while the FFNN model uses the fuzzy logic conditions to estimate the distance.

Correa et al (2016) have proposed a user's position technique that estimates the position of the user based on the Received Signal Strength Indicator (RSSI) without magnetometers.

Al-Jarrah et al (2016) have designed an embedded blimp robot to estimate the localization of users and track the target in the sensor network. The efficiency of the network system is improved.

III. SPATIAL DIVISION CLUSTERING

Spatial Division Clustering (SDC) increases the position accuracy in a sensor network. SDC involves the Genetic Algorithm (GA) based Support Vector Machine (SVM) techniques. This technique uses the bionic process for optimization of SVM. This technique involves three steps such as selection, crossover and mutation.

During the initialization phase, nodes are deployed and Cluster Heads (CHs) are assigned to each cluster. Crossover is done to establish connection and carry out data transmission between the sensors. Mutation is involved in collecting the required data after data transmission. The main drawback of this technique is that, it involves more delay and drop rate.

Semi-supervised Affinity Propagation (SAP) technique is used to localize sensors using clustering. The Received Signal Strength (RSS) is collected from the mobile sensors from which the fingerprint distance between the sensors and the user nodes are calculated. The nearest neighbor is chosen at random and the isolated points are detected. SAP technique is applied to choose the CHs. They are involved in the localization of sensors.

IV. PROPOSED METHOD

In this paper, Clustered Positioning for Indoor Environment (CPIE) is proposed to increase the accuracy of the position of the sensor nodes in the WSN.

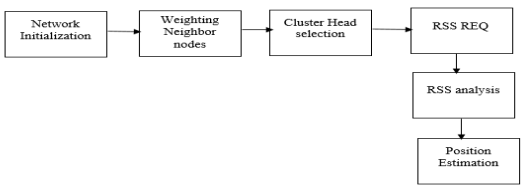

Fig. 1 Flow chart of Clustered positioning for indoor environment (CPIE)

This technique involves initialization, weighting of neighboring nodes, CH selection, RSS request propagation, RSS analysis and position estimation.

Figure 1 shows that the flow of CPIE.

- ✓ During the network initialization phase, as already mentioned, the nodes are deployed and a WSN is formed for indoor environment.
- ✓ During the next phase of weight computation, the weights of each node to its neighbors in the sensor network are computed.
- ✓ The node which has more numbers of neighboring nodes is elected as the CH. CHs are elected for each floor and are connected in parallel.
- ✓ All the CHs send the RSS request to all the cluster members in their group. The cluster members respond to the RSS request.
- ✓ Based on the responses from the cluster members, the CHs estimate the position of the sensors based on the RSS.

V. NETWORK MODEL

The network architecture shows the deployment of sensors in each floor in the indoor building. Figure 2 shows the network model and the stable and mobile nodes in each floor. Both the stable and mobile nodes are involved in the calculation of weights of the neighbor nodes, based on which the neighbor with the largest weight is chosen as the CH.

The CHs on each floor are connected. Communication between members of a cluster with members on the same/ other floors is only through the CH.

A. Identification of neighbor nodes

The neighbor nodes are identified as follows.

In each floor, 'S_n' sends the request to the sensors within the range of communication. A node that receives the request, responds, based on which connection is established.

$$\prod_{i=1}^{n} F_i C \cup_{x=1}^{m} \{s_n(x)\} \quad (1)$$

F_i - Floors, i = 1, 2,…, n

$S_n(x)$ - Sensor node, for x = 1, 2,…,m

Sensor nodes send the route request to all the neighboring nodes. Based on the reply from the neighboring node, the weights for each sensor are calculated by taking into account the number of responses from the neighbor nodes.

$$S_n(x), x \in m = \sum_{x=1}^{m} \sum_{z=1}^{k} \mathrm{RREPz}\{\mathrm{Nei}\{S_n(x)\}\} \quad (2)$$

The nodes that respond to the request from a particular sensor node establish wireless links between those sensors.

$$N_c \sum_{x=1}^{m} S_n(x) = \sum_{k=1}^{z} L(k) + \sum_{b=1}^{z} Ne(b) \quad (3)$$

L(k) - Link between the nodes

Ne(b) - Number of neighbor nodes connected to the particular sensor node

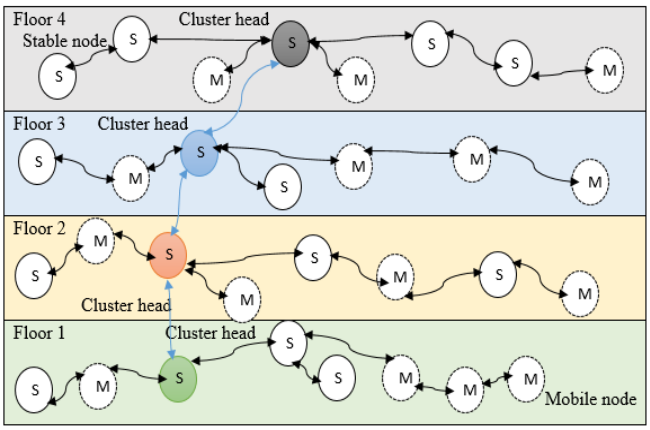

Fig. 2 Proposed Network Model

B. Cluster Head Selection

The Cluster Head (CH) is selected by comparing the neighboring nodes of each sensor. The sensor with highest number of neighbor nodes is elected as the CH. If more than one node has the same number of neighbor nodes, the node that is stable is selected as the cluster head.

$$\mathrm{Ch} \rightarrow N_c(i) \gg N_c(j) \quad (4)$$

$$\mathrm{Ch} = i.\max_{x \in N} N_c(ix) + \max_{y \in N} N_c(jy) \quad (5)$$

For example, consider the number of neighbors of each sensor in a floor.

Let, $N(S_1) = 3, N(S_2) = 2, N(S_{31}) = 1$. In this case, '$S_2$' will be the CH. If suppose, $N(S_1) = N(S_2) = 3$. If 'S_1' is stable and 'S_2' is mobile, then 'S_1' will be given more priority. The stable condition will check the mobility of each node. If the mobility of a node is 0m/s, it is considered as a stable node, and if the mobility greater than or equal to 1m/s, it is considered as a mobile node.

C. RSS analysis

The RSS of each node is analyzed to estimate the position of the sensors. After the selection of CH, it sends the RSS request to their cluster members. Based on the response from the members, the CH finds the position of the sensors with the RSSI. That is known as fingerprint indoor positioning model.

$$\mathrm{Ch.RSS_{req}} \rightarrow \sum_{x=1,\in Fi}^{m} S_n(x) \quad (6)$$

In the proposed Clustered Positioning for Indoor Environment (CPIE), the CH estimates the position of the sensors based on the RSSI. The CH sends the Route REQuest (RREQ) to all the members of the cluster in the respective floor. It considers the RSSI of each node to locate the position of the sensor.

Based on the position estimation, all the nodes transmit data to their destination. If any node moves out to another floor, the CH in that floor will include the node to its cluster.

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The position of the new node is analyzed using RSS analysis, and the CH informs the position of the node to the cluster members. This mechanism involves less delay and drop rate.

D. Mathematical Analysis

Network creation is based on the 'x', 'y' and 'z' coordinates. The value for each node is estimated by the below equation.

$$n = \prod_{i,j,k=1}^{T} N\{X(i); Y(j); Z(k)\} \quad (7)$$

where,
n- node
N- Network topography
t- topography limit

Within the network topography, nodes are deployed based on 'x', 'y' and 'z' coordinates with respect to 'i', 'j' and 'k' values within the topography limit.

The source and the destination nodes are selected from the topography. The area is calculated using the 3D coordinates taken from the RSS.

$$Aq(X, Y, Z) = \sum_{n=1}^{k} 1/2(|X_n * Y_n||X_n * Z_n|)\text{Sin}\theta \quad (8)$$

The area is calculated from the RSS. The position is estimated from the 3D coordinate values calculated using the Equation (8).

Based on the RSS of the cluster members derived from the response of the nodes, the position of the sensors are estimated. The positions with similar values are found.

Consider the 'z' coordinate as zero. By getting the 'Aq' area level of the 'x', 'y' and 'z' coordinates, the distance between the neighbors are computed as shown in Equation (9).

For i = 1….n,

$$D = \sqrt{\sum_{i=1}^{n}\{Aqi(Y) - Aq(X)\} * \{Aqi(Y) - Aqi(X)\}} \quad (9)$$

Using the position estimation equation, the position and the coordinate of each node are estimated. From the coordinates, the distance between the nodes is computed.

VI. RESULTS AND DISCUSSION

The performance of the proposed Clustered Positioning for Indoor Environment (CPIE) is analyzed by varying the number of floors in the indoor environment. CPIE-FI is analyzed for four floor levels, CPIE-FII is analyzed for 8 floor levels and CPIE –FIII is analyzed for sixteen floor levels.

The topography is taken as 1000 * 1000 m. The physical layer type is set as wireless medium and the energy level of each node is set. The simulation time is taken 200 seconds and the number of nodes is varied from 100 to 500. The performance of CPIE is compared with the existing techniques like Spatial Division Clustering (SDC) and Semi-supervised Affinity Propagation (SAP). It is seen that CPIE outperforms SDC and SAP in terms of localization error, network efficiency and delay.

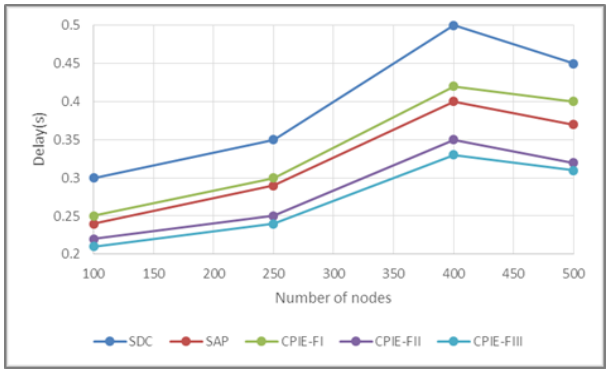

Fig. 3. Delay Analysis

Fig. 3 shows that the delay involved in transmitting the data from one sensor to another. CPIE involves less delay. SDC and SAP involve more delay due to diversity problems and propagation model respectively. As CHs monitor the cluster members, CPIE involves less drop rate and delay.

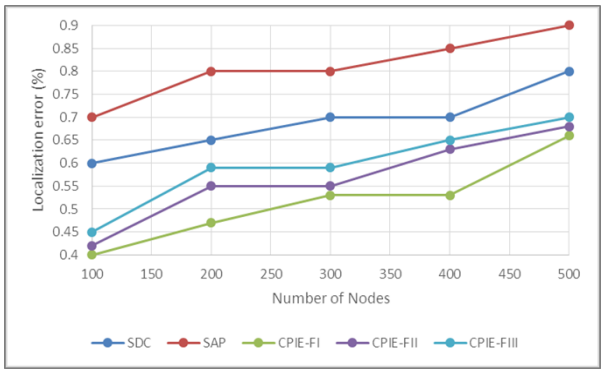

Fig. 4. Localization Error

Fig. 4 shows the localization error due to the deviation in the location estimation in contrast to the original configuration. Generally, when estimating the location, a marginal variation either a plus or a minus error from the exact localization is expected. In all the cases, the error increases as the number of modes and distance increase. The proposed mechanism CPIE involves reduced localization error which is almost half when compared to the existing techniques SDC and SAP, and at a maximum of 0.7% for 500 nodes.

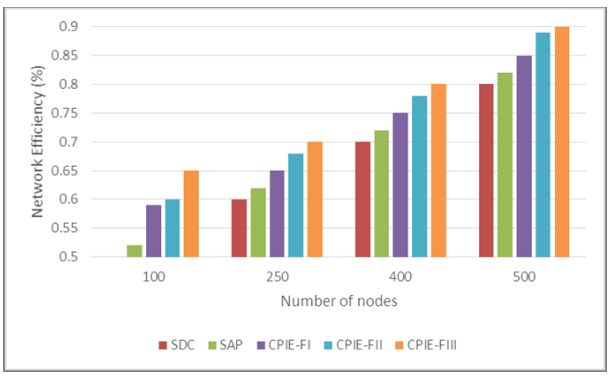

Fig. 5. Network Efficiency

Fig. 5 shows that the network efficiency which is the ratio of the number of packets successfully received to the number of packets transmitted. SDC and SAP offer lesser network efficiency, whereas the proposed CPIE technique increases the network efficiency even when the number of floors is increased in the same building. This technique offers 85% to 90% increased network efficiency for varying number of floor levels in the indoor environment.

VII. CONCLUSION

The proposed Clustered positioning for indoor environment (CPIE) yields better network performance even when the number of floors in the indoor environment is increased. It involves less delay and low localization error, and offers improved network efficiency in contrast to the existing techniques such as spatial division clustering (SDC) and Semi-Supervised affinity propagation (SAP) have.

Based on the response from the members in a cluster, the RSSI information is obtained by the CH, which in turn estimates the exact position of the sensor nodes in each floor. By identifying the exact positions of the cluster members, the CH establishes effective communication among the nodes resulting in improved performance.

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