Sensor Localization using Signal Receiving Probability and Procrustes Analysis

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Abstract: The location information of sensors is of great importance for wireless sensor network automation and has been one of the major challenges in large-scale sensor networks. In order to improve the localization accuracy of sensors, the gain of both range-free and range-based approaches need to be concerned. In this paper, we propose a new localization algorithm based on signal receiving probability and Procrustes analysis. A critical observation in range-free technique is sensors can move a non-zero distance without changing it's connectivity information. To defeat that difficulty and achieve a better ranging measurement, a receiving probability function, which is sensitive to the distance, is used in this paper. The probability function is used to calculate the topological coordinates and then to transform it to physical coordinates, the Procrustes analysis is used. The result shows that our proposed algorithm has been able to calculate the physical coordinates of sensors, which are distributed over an area, consist of obstacles and with different environmental conditions. Moreover, it outperformed the other existing algorithms by a maximum localization error less then 2m.

1 INTRODUCTION

Wireless Sensor Networks (WSNs) applications cover a large number of domains spanning environmental monitoring, military, agriculture, transportation and inventory tracking (Garca-Hernndez et al., 2007) (Tubaishat and Madria, 2003). Future WSNs will be large-scale networks automated to self-organized and perform a specific task. Thus, the location map of the sensors is required.

However, finding the locations of the sensors is crucial and has received substantive attention in recent years. The algorithms used to calculate the physical coordinates of the sensors can be divided into two categories, namely Range-based and Range-free localization algorithms. Range-based algorithms use special hardware component to measure range-based parameters such as received signal strength (RSS) (Chengdong et al., 2011), time of arrival (TOA) (Wang and Ho, 2013), angle of arrival (AOA) (Kotwal et al., 2010). These algorithms are affected by noise, fading and interference, and as a result, their accuracy decreases in environments with obstacles. Range-free algorithms rely on the information about the connectivity of the sensors instead of using special hardware device. However, the accuracy of the algorithms is highly depended on the number of anchor nodes i.e. nodes known their locations, and their distribution.

To this end, we are proposing a localization algorithm based on Receiving Probability and Procrustes Analysis (RP-PA). Here we are trying to achieve the advantages in both range-based and range-free techniques. As in range-free algorithms we do not use any special hardware component, but to calculate the distances, a signal receiving probability function that is sensitive to the distance is used. Since we are not using any hardware component to measure the distances, the hardware cost of the network can minimize.

RP-PA algorithm uses a receiving signal probability function to reduce the dependency on range-based measurements. It starts from finding the topology map of the network using the probability function. Topology map is an arrangement of nodes without affecting it's connectivity information. In RSSI based algorithms, the distances are extracted from receiving power that encounters some error due to RF communication effects. Thus, we evaluate the connectivity information without taking those error prone parameters. In range-free algorithms, they consider the

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connectivity information with the hop counts to the anchor nodes, but it is not sensitive to the distance. As a result, it is possible to move a sensor node over a non-zero distance without changing the hop count. Hence, range-free algorithms generate physical coordinates with less accuracy. To overcome this problem, we construct the connectivity information matrix using a probability function, which is sensitive to the distance between sensor nodes.

To transform the topology coordinates to physical coordinates, the algorithm uses the Procrustes Analysis. From the result, it can be seen that the proposed RP-PA algorithm is able to provide accurate physical coordinates of the sensors. Also, it results in an error less than 2m and outperforms the RSSI and hop-based localization algorithms.

2 BACKGROUND

Prior work on localization techniques, can be grouped into two categories range-based and range-free localization. In range-based techniques special hardware device is used to measure the range-based parameters such as signal strength, time of arrival and angle of arrival. In received signal strength indicator (RSSI) based localization algorithms, signal strength of receiving packets is used to estimate the distance between nodes. The distance calculation of these algorithms use two models namely, theoretical and empirical models (Zhang et al., 2012). In theoretical models, RF signal transmission loss model is used to directly calculate the distance between two nodes (Mukhopadhyay et al., 2014)(Al Alawi, 2011). The empirical models, use a two steps process to obtain the location. First, they create an offline RSSI database, using anchor nodes. Secondly, it determines the coordinates of non-anchor nodes by matching the received signal strength to a record of the database (Chengdong et al., 2011)(Wanga et al., 2011).

The localization method based on time difference of arrival (TDOA) estimates the coordinates of an unknown node by anchor nodes' coordinates and time difference of arrival from those anchors to the node. For the calculation, it needs at least four anchors (Savarese et al., 2002) (Luo et al., 2012) (Liu et al., 2012) (Wang and Ho, 2013) (Huang et al., 2015). Furthermore, in time of arrival (TOA) based localization, the anchor nodes broadcast a signal and the sensor nodes that receive these broadcasts, use the time difference of arrival , RSS and a the angle of arrival to determine their locations. This requires the sensor timers have to be synchronized. To overcome this requirement, researchers have proposed the use of Round-Trip TOA (RTOA) (Wymeersch et al., 2009) and Two Way TOA (TW-TOA) (Gholami et al., 2012)(Oguz-Ekim et al., 2013). Again, TOA localization does not address issues associated with obstacles and RF signal transmission affects.

In range-free localization algorithms, the locations of nodes are obtained without using any special hardware. They rely on the connectivity information of nodes. First, it gets the distance in hops and then maps the hop distance to geometric distance (Niculescu and Nath, 2003)(Tian et al., 2003)(Liu et al., 2004) using anchor node locations. Therefore, the accuracy of these algorithms highly depends on the number of anchor nodes and their deployment. The key issue of range-free algorithms is the distance estimation i.e. the mapping of the hop distance to geometric distance.

Dulanjalie et al. (Dhanapala and Jayasumana, 2014) presented a method to obtain topology-preserving maps of WSNs using virtual coordinates (VCs) of sensor nodes. Topological mapping techniques are fundamentally different to localization techniques because the mapping algorithms are concerned with the arrangement of the nodes. They are not concerned about the actual location of the nodes. In other words, the mapping schemes expect the relative distances to be accurate, not the physical distances. Thus, given the absolute position of a subset of nodes, global localization is realizable. However, to achieve this, the topological map should be isomorphic to the physical layout of the sensor network. In Virtual Coordinate System (VCS), the layout information such as physical voids, shape, and etc. are absent. Furthermore, Dulanjalie et al.(Dhanapala and Jayasumana, 2014) have shown that transformation for topological map from virtual coordinates can be generated using a subset of nodes. However, when the number of nodes increase, the time required to generate the virtual coordinate matrix also increases.

3 DETAILS OF THE PROPOSED ALGORITHM: RP-PA

This section describes the work flow of RP-PA algorithm, that calculates the physical coordinates of the sensors. The physical map is achieved by using the packet receiving probability function and Procrustes transformation. RP-PA algorithm consider two aspects i.e. accuracy of range measurements and the accuracy of the coordinate. The range measurement accuracy is obtained by the receiving signal probability function sensitive for the distance. First using the probability values, the topological coordinates of each node is calculated. Then to achieve the localization accuracy, Procrustes analysis is carried out in each node. The detail of the algorithm is described in following subsection.

3.1 Topological Coordinates

The first task of the RP-PA algorithm is to calculate the coordinate of nodes in topological map. Topology map represents the arrangement of nodes without affecting the connectivity information of nodes. To find the connectivity information, receiving probability function, which describes below, is used.

3.1.1 The Receiving Probability Function

This function describes the probability of packet receiving from sensor when anchor node is located at a particular distance. Let, $S(d)$ be the probability value when anchor node is at distance d from the sensor. Then, $S(d)$ satisfies the following constraints:

$$\begin{aligned} 0 \leq S(d) \leq 1 \quad \forall d \\ S(d_1) \leq S(d_2) \quad \forall d_1 \geq d_2 \\ S(d) = 0 \quad \forall d > R \end{aligned} \tag{1}$$

where $R > 0$ is some given distance.

Such a function $S(d)$ is called the receiving probability function. We will use the following example of such a function:

$$\begin{aligned} S(d) &:= p_0 \quad \forall d \leq r \\ S(d) &:= 0 \quad \forall d \geq R \\ S(d) &:= \frac{p_0(R-d)}{(R-r)} \quad \forall r < d < R \end{aligned} \tag{2}$$

where $0 < p0 \leq 1$, $0 < r < R < R_c$ are some given constants. R_c is the communication range of a sensor node. It is obvious that the function (2) satisfies all the conditions (1).

The receiving probability function we are using is an intermediate model of RSSI signal receiving and hop-based packet receiving. As shown in Figure 1, it can be seen that hop based algorithms use the $r = R$ assumption, which cannot be achieved in real environment. On the other hand, RSSI localization uses a polynomial function to estimate packet receiving probability, which is hard to estimate the parameters for different environmental situations. Therefore, here we consider an intermediate level between RSSI model and VC model to obtained the topological coordinates.

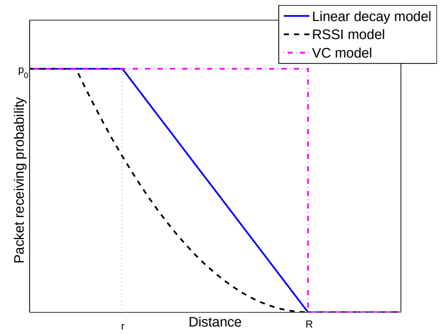


Figure 1: Packet receiving probability function for different models.

3.1.2 Calculating Topological Coordinates

This section describes the topological coordinate calculation using the receiving probability function. Let consider a network consist with N number of steady sensors in unknown locations labeled $i = 1, 2, ..., N$ and $M(< N)$ number of steady anchor nodes that know their locations labeled A_j, $j = 1, 2...M$. The anchor nodes transmit signals at times $t_1 < t_2 < ... < t_S$ to it's one-hop neighborhood. We introduce a binary matrix M_i of order $a \times S$ by the following rule. Here, a is the number of anchor nodes in node i's neighborhood.

$M_i(j,s) = 1$, if node i gets a signal from the anchor A_j at the time t_s;

$M_i(j,s) = 0$, if node i does not get a signal from the anchor A_j at the time t_s.

Then, based on the M_i matrix, signal receiving probability matrix RP_i of order $a \times 1$is deduced as follows.

$$RP_i(j,1) = \frac{\sum_{s=1}^{S} M_i(j,s)}{S} \tag{3}$$

Finally, based on the anchor node positions, the receiving probability function $S(d)$ and the receiving probability matrix RP_i, we obtain the topological coordinates of the sensors. Let $AP_i(1,1), AP_i(2,1), ..., AP_i(a,1)$ denote the elements of the vector AP_i. Furthermore, the probability for a sensor node to receive a signal from a anchor node A_j is described by the function $S(d)$ where d is the distance between the anchor and the sensor node i at the time of sending the signal. Thus we can map the probability values to a distance vector using the receiving probability function denoted as $d_i(1,1), d_i(2,1)...d_i(a,1)$ respectively.

After knowing the distance of the vector of sensor i, we have used trilateration to calculate the coordinate of the node with respect to the anchors in its first hop neighborhood. The coordinates of the anchors in node i's first hop neighborhood are

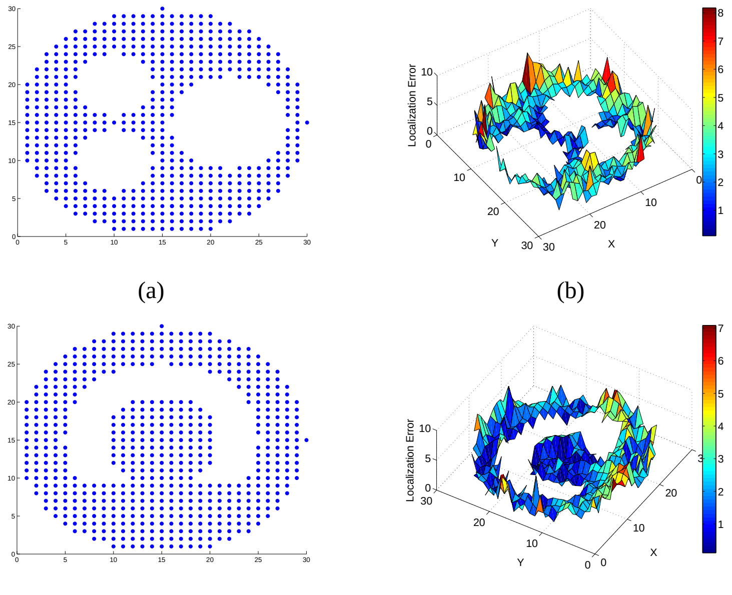


Figure 2: (a) Circular-shaped network, (b) Error distribution, (c) Concave void network and (d) Error distribution.

$(x_1,y_1),(x_2,y_2)...(x_a,y_a)$. The topological coordinate of the node i is (x_i^t,y_i^t) is given by the equation 4.

$$AX^t = B \tag{4}$$

where,

$$A = \begin{bmatrix} 2x_i^t(x_a - x_1) & 2y_i^t(y_a - y_1) \\ 2x_i^t(x_a - x_2) & 2y_i^t(y_a - y_2) \\ \vdots & \vdots \\ 2x_i^t(x_a - x_{a-1}) & 2y_i^t(y_a - y_{a-1}) \end{bmatrix}$$

,

$$X^t = \begin{bmatrix} x_i^t \\ y_i^t \end{bmatrix}$$

and

$$B = \begin{bmatrix} (x_a^2 - x_1^2) + (y_a^2 - y_1^2) + (d_i(a,1) - d_i(1,1)) \\ \vdots \\ (x_a^2 - x_(a-1)^2) + (y_a^2 - y_(a-1)^2) + \\ (d_i(a,1) - d_i(1,1)) \end{bmatrix}$$

,

To find an optimal topological coordinates of the sensors, we used the Least square approximation. Here the objective function is given as in condition 6 and by solving to X^{*t} we got the solution as in equation .

$$Min \parallel AX^{*t}B \parallel^2 \tag{5}$$

$$X^* = (AA)^{-1}(A)B \tag{6}$$

where, $X^* = [x_i^{*t}\, y_i^{*t}]^T$

3.2 Obtaining Physical Coordinates using Procrustes Analysis

This section describes the transformation of topological coordinates to physical coordinates using Procrustes analysis. Procrustes Analysis is used to align two sets of data points. Here we used it to obtain physical coordinate of sensors from the topological coordinates that is calculated in the previous section.

Procrustes analysis calculates the scaling factor, rotation angle and shift between the two sets (Nhat et al., 2008). If the transformation between the two sets is not linear, Procrustes analysis will find the transformation which has an error. Thus we need to make sure that topological coordinates have linearized error with the actual sensor location. Figure 2 shows the error distribution of the topological coordinates with respect to the actual positions of the sensor nodes. According to the figure, the error distribution is not linear for the whole network. Hence, a single transformation can not be applied to the whole network.

To overcome that problem, transformation factors are calculated in each node based on it's one hop anchor nodes. Let consider sensor node i have a number of anchor nodes in it's first hop neighborhood. Then X and Y are the topological and physical coordinate matrices with length of $a \times 2$ respectively. Thus the transformation factors of node i can be estimated by equation 7.

$$Y = bXT + c; \quad (7)$$

where b is the scaling factor, T is the rotation angle and c is the shift value. When the transformation factors are estimated, node i can calculates it's physical coordinates using the equation 7 where X is the topological coordinates of node i and Y is the physical coordinates of node i. Figure 3 compares the localization error before and after the Procrustes analysis. In this experiment, we can see that each node uses a different transformation factor to calculates it's physical coordinates. Thus the localization error has been reduced.

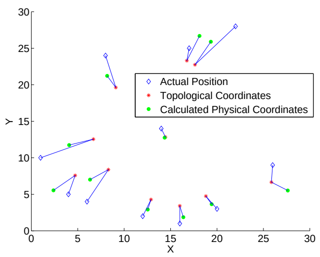


Figure 3: Impact of Procrustes Analysis.

4 RESULT

The performance of the proposed RP-PA algorithm is evaluated in this section. First the receive signal strength model used for the simulation is described. Then the performance of the algorithm is compared with other existing algorithms. MATLAB simulation software was used for the computations.

4.1 Receive Signal Strength Model

The received signal strength can be modeled as having two components such as path loss and shadowing (Pathirana et al., 2005). Therefore, the commonly used propagation model of RF signals is given in equation (8).

$$P_{rx,i}(t) = P_{tx,j} - 10\varepsilon log d_{ij}(t) + v_i(t) \quad (8)$$

where, the received signal strength at node i at time t is $P_{rx,i}(t)$, the transmitted signal strength of the signal at node j is $P_{tx,j}$, the path-loss exponent is ε, the distance between node i and node j at time t is $d_{ij}(t)$ and the logarithm of shadowing component on node i at time t is $v_i(t)$.

However, this model is not suitable for a network with some obstacles. In (Lott and Forkel, 2001), they proposed a MultiWall-Multifloor Model for RF communication. In this model the variation of the absorption against the thickness of the medium which signal traverse, is not considered. Therefore we updated the equation (8) by using the Lambert-Bouguer law. Let $L_{ob,i}(t)$ is the loss due to signal absorption from obstacles exist in the line of sight of node i and j at time t, then the RF signal propagation model is as in equation (9).

Table 1: Simulation Parameters.

Parameter	**Value**
Transmitted power	-50dB
Sensitivity	-90dB
Communication radius	10m
Suburban area	ε = 2.7 σ =9.6
Light tree density area	ε = 3.6 σ =8.2

$$P_{rx,i}(t) = P_{tx,j} - 10\varepsilon log d_{ij}(t) - L_{ob,i}(t) + v_i(t) \quad (9)$$

The absorption coefficient and the thickness of the obstacle medium, which signal traverses are α and $d_o(t)$ respectively. Then $L_{ob,i}(t)$ can be calculated as,

$$L_{ob,i}(t) = \Sigma_{k=1}^{n} 10\alpha d_o(t) log(e) \quad (10)$$

where, n is the number of obstacles exist in between node i and node j.

4.2 Performance Evaluation

The performance of the receiving probability approach and other two localization approaches, that are RSSI based(Mukhopadhyay et al., 2014) and hop based (Dhanapala and Jayasumana, 2014), is evaluated through large-scale simulations. To make the caparison equitable for all three approaches, the Procrustes analysis is applied to each output obtained from the above three approaches.

The large-scale WSNs we selected for the evaluation is shown in Figure 4 and 5 . Here we have different shapes of networks with obstacles. The Figure 4(a) is a 496 sensor nodes circular-shaped network in a suburban area with three physical obstacles (concrete barriers). The Figure 5(a) is a 554 sensor nodes network with a concave void (concrete barriers) in a light tree density area. Table 1 presents the simulation parameters. Here we consider anchor nodes are randomly distributed over the network area.

Figure 4 and 5, clearly demonstrate the effectiveness of the proposed algorithm. However to compare the performance of the algorithm, we calculate the localization error as in the equation 11. Figure 6 com-

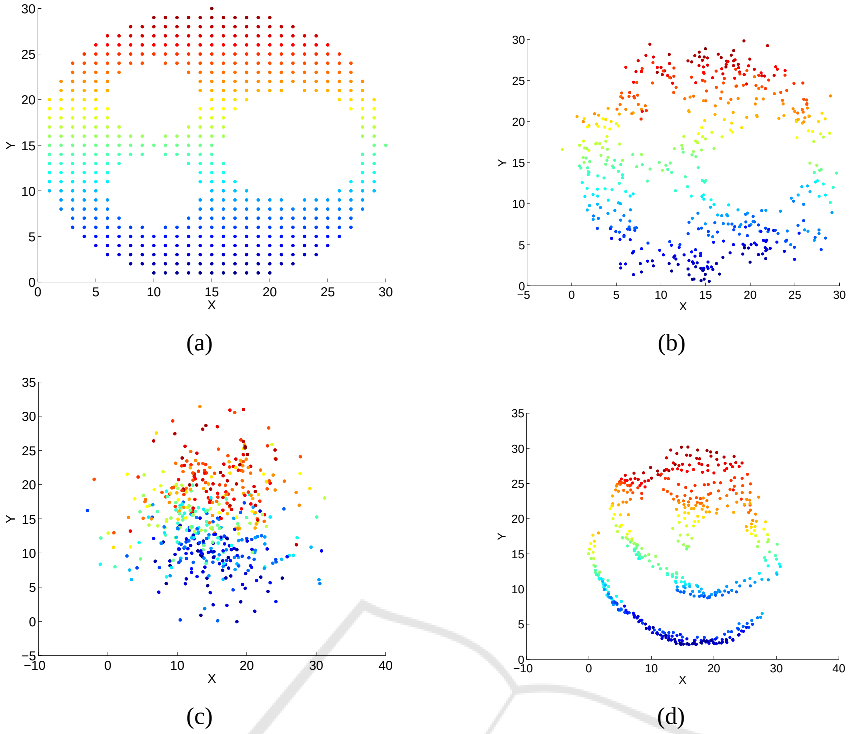


Figure 4: (a) Circular-shaped network with 496 nodes , (b) Output of proposed RP-PA algorithm, (c) Output of RSSI algorithm and (d) Output of Hop based algorithm.

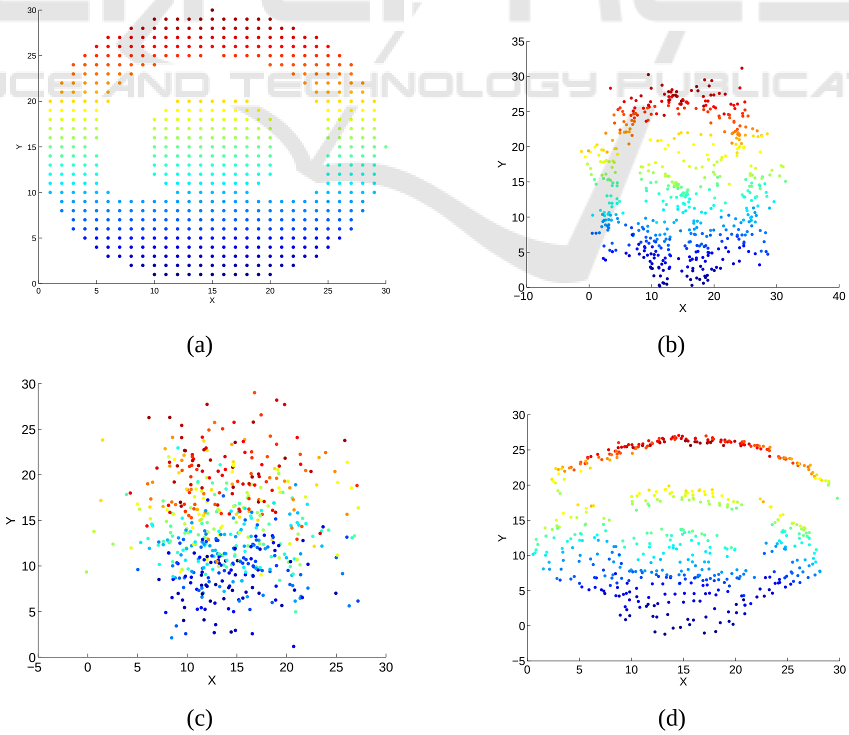


Figure 5: (a) Circular-shaped concave void network with 554 nodes , (b) Output of proposed RP-PA algorithm, (c) Output of RSSI algorithm and (d) Output of Hop based algorithm.

pares the localization error of the three methods mentioned above for the two network distributions. It can be seen that the proposed RP-PA algorithms outperforms the other two methods by having a average localization error less than 2m.

$$location_{e}rror = \frac{\sum_{i=1}^{N} \sqrt{(x_i - x_i^t)^2 + (y_i - y_i^t)^2}}{N} \quad (11)$$

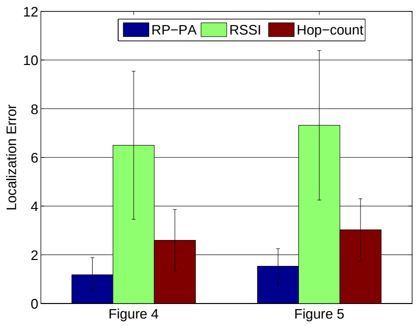
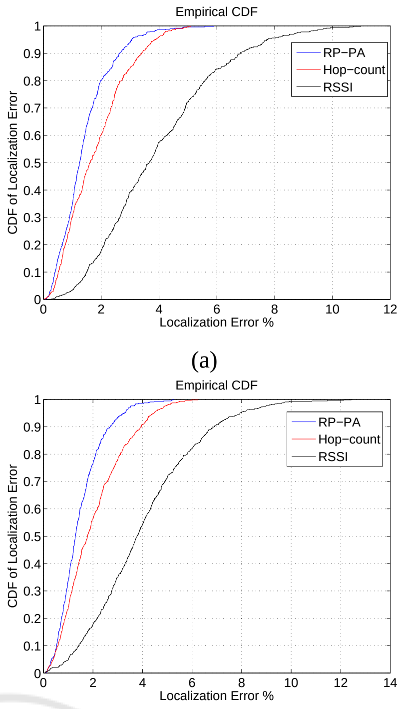


Figure 6: Localization error comparison.

Moreover, to analyze the localization error more enormously, Figure 7 compares the cumulative distribution of the localization error of three methods for the two networks. From Figure 7(a) and Figure 7(b), it can be seen that 80% of nodes have less than 2m localization error with RP-PA algorithm. Hence it is seen that RP-PA algorithm performs better than RSSI and hop based localization algorithms.

Figure 8 shows the performance of the RP-PA algorithm against the number of anchor nodes. According to the figure, RP-PA algorithm has been able to generate physical coordinates of sensor nodes with less than 2m average localization error for the two network deployed in different environmental situations using 10% of anchor nodes. Thus, with less amount of sensor nodes, the algorithm can calculate the location of sensors in a large-scale WSN.



(b)

Figure 7: (a) CDF of localization error in Figure 4 network, (b) CDF of localizatio error in Figure 5 network.

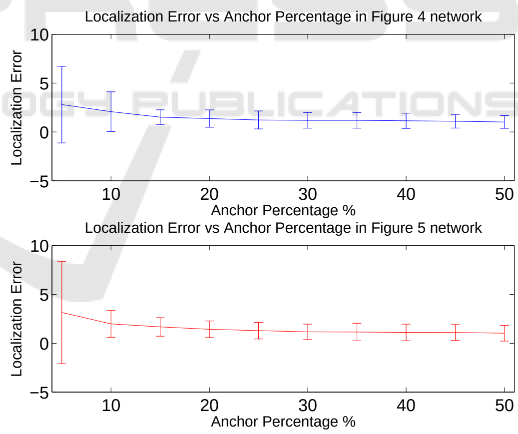


Figure 8: Localization error against the anchor percentage with respect to the total number of nodes.

5 CONCLUSION

We presented a RP-PA algorithm, which calculates the coordinates of sensor nodes without using any special hardware component. RP-PA algorithm extracts the advantages if range-based and range-free localization techniques. In range-free approach, the connectivity information is obtained by hop-count matrix and as a result sensors can move non-zero distance without affecting the connectivity information. However in range-based algorithms, RF communication effects such as noise, fading and interference affect the range measurements. To defeat these issues, we generate a topology map i.e. arrangement of nodes, using a signal receiving probability function that is sensitive to the distance. Then the topology coordinates are transformed to the physical coordinates using Procrustes analysis. Due the obstacles exist in the network; the transformation is not unique through out the whole network. Thus we calculate the transformation factors in each sensor node.

The result shows that the RP-PA algorithm calculate physical coordinates of sensors with localization error less than 2m and it outperforms RSSI and hop-based localization algorithms.

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