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Hybrid RSS-SOM Localization Scheme for Wireless Ad Hoc and Sensor Networks

Nyein Aye Maung Maung
Graduate School of Information Science and Engineering
Ritsumeikan University
Kusatsu, Japan
Email: gr042065@ed.ritsumei.ac.jp

Makoto Kawai
Graduate School of Information Science and Engineering
Ritsumeikan University
Kusatsu, Japan
Email: kawai@is.ritsumei.ac.jp

***Abstract*—Localization of wireless ad hoc and sensor networks has gained much research attention for several years. This paper proposes a hybrid localization scheme which exploits Received Signal Strength (RSS)-based ranging and Self Organizing Maps (SOM)-based range free localization methods to obtain the trade-off between cost, power and location accuracy. Distance information from RSS measurement has been utilized in the learning steps of SOM-based localization algorithm to get more accurate location estimates while reducing the number of learning steps. Methods on RSS uncertainty reduction and obstacle filtering are also incorporated in the proposed RSS-SOM scheme. Results from extensive simulations prove that our proposed hybrid solution outperforms several existing localization algorithms in both isotropic and anisotropic network environments with lower anchor utilization.**

Keywords-component; RSS; SOM; Localization;

I. Introduction

Accurate and low-cost network localization is a critical requirement for the deployment of wireless ad hoc and sensor networks in a wide variety of applications like disaster management and environmental monitoring, health care, industrial process control, military battlefield awareness, security and surveillance. So far, there have been many node localization algorithms for wireless ad hoc and sensor networks. The current localization algorithms can be labeled into two categories: range-free algorithms [1] and ranging algorithms [2] based on whether the range measurements are used or not.

Range-free schemes determine the node's location by using connectivity information, the number of hops between nodes and node distribution density, without any specific hardware support. The main advantages of these approaches are lower cost and less power consumption since additional hardware resources are not required. But such mechanisms typically need a large number of anchors with known location and specific node deployments. Our previous works [3, 4] proposed SOM-based localization methods to solve these problems and showed better location accuracy.

More precise location estimation can be achieved by ranging approaches which are typically based on RSS, time-of-arrival (TOA), time-difference-of-arrival (TDOA), angle-of-arrival (AOA), or their combinations. These kinds of localization methods have higher accuracy, but the negative point is that each sensor node must be equipped with additional hardware for ranging, thus consuming more power and additional cost.

Thanks to the advances in technologies that the RSS indicator (RSSI) has become a standard feature in most wireless devices [5]. Combined with the facts that RSS based localization techniques require no additional hardware, and are unlikely to significantly impact on low power consumption, sensor size and thus cost, the use of RSS as a distance estimation technique has led to a number of RSS-based localization algorithms. However, researchers have expressed doubts on the reliability of RSS measurements [6]. More work on that problems includes RSS fingerprinting based approach [7] which requires an offline radio map that contains measured RSS patterns from all visible anchors at certain locations. But a high number of anchor utilization and the need for fixed or preconfigured network environment are the downsides of this approach. Hybrid schemes like RSS-DVHOP [8] and SRSSQ [9] were proposed to apply cost effective RSS into the range free localization algorithms. However, method proposed in RSS-DVHOP requires a relatively high density of anchors in the network. SRSSQ uses indirect mapping of RSS into different radio range levels to improve the location estimation accuracy of the range free algorithms.

The aim of this paper is to provide a new hybrid localization scheme which gives higher localization accuracy while reducing cost, power and anchor utilization, and supporting dynamic node placements. As motivations to previous SOM-based works where only connectivity information among neighboring nodes are applied, our proposed scheme utilizes RSS-based distance information to estimate relative location of nodes. Furthermore, it uses the information from multi-hop anchors in calculating absolute location for nodes. To smooth out the RSS instability, a mean filter has been utilized in our solution. Impacts of obstacle and irregular network shape have also been considered in the proposed solution. Simulations on various network topologies, node density, and anchor utilization have been carried out and the results show a high degree of accuracy compared with other existing works. The rest of the paper is organized as follows: section II describes RSS-based ranging technique for the distance estimation. Proposed hybrid RSS-SOM scheme is presented in section III and section IV provides simulation evaluations and results. Finally in section V, we summarize our results and discuss the future works.

II. RSS-based Distance Estimation

A. Radio Propagation Model

Radio propagation model used in our research is the log-normal shadow model [10] which is a more general propagation model suitable for both indoor and outdoor environments. This model provides a number of parameters which can be configured according to different environments. The calculation formula is as follows:

$$P_R = N(\overline{P_R}, \sigma_{dB}^2) \tag{1}$$

where P_R is the signal strength of the received packet (RSS) at the receiving node, and σ_{dB}^2 is the variance of the shadowing. From (1) and following the derivation steps shown in [11], P_R can be related to the distance between the two communicating nodes *i* and *j* by the following expression:

$$P_{R_{ij}} = P_{ref} - 10 n_i log_{10}(\frac{d_{ij}}{d_0}) + X_\sigma \tag{2}$$

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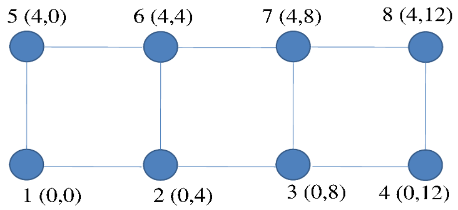


Figure 1: Node placement.

where d_{ij} is the distance between the two nodes, n_i is the path-loss exponent corresponding to the propagation channel, and X_σ denotes a zero mean Gaussian random variable with standard deviation σ caused by shadowing. The term P_{ref} is the power measured at a reference distance d_0 which is set to 1. Then, (2) becomes

$$P_{R_{ij}} = P_{ref} - 10 n_i log_{10} d_{ij} + X_\sigma. \tag{3}$$

From (3), the distance between a transmitter and a receiver can be estimated from $P_{R_{ij}}$ as

$$d_{ij} = 10^{\frac{P_{ref} - P_{R_{ij}} + X_\sigma}{10 n_i}}. \tag{4}$$

B. Filtering RSS Values

Estimating the distance from a single RSS measurement is erroneous due to RSS variability. Various filters can be used to smooth out the RSS variability and to remove fast fading term over a time interval. Two common filters are simple averaging (mean) filter and feedback filter [12]. For the mean filter, in time instants t = 1 to k in which we can assume that the distance and the environment between the two communicating nodes do not change significantly, the mean filter simply calculates the average of RSS values ($\bar{P}_{R_{ij}}$) by

$$\bar{P}_{R_{ij}} = \frac{1}{k} \sum_{t=1}^{k} P_{R_{ij}}(t). \tag{5}$$

The feedback filter uses only a small part of the most recent RSS values for each calculation illustrated as follows:

$$\bar{P}_{R_{ij}} = \alpha P_{R_{ij}}(t) + (1-\alpha) P_{R_{ij}}(t-1) \tag{6}$$

where $\alpha \geq 0.75$. Then the distance measurement in (4) turns as follows:

$$d_{ij} = 10^{\frac{P_{ref} - \bar{P}_{R_{ij}} + X_\sigma}{10 n_i}}. \tag{7}$$

To evaluate the performance of each filter, we have measured the RSS of packets arriving at node 1 from node 2 which is deployed as illustrated in Fig. 1. As well, the distance between node 1 and other nodes are calculated based on (7) using RSS output from mean filter, feedback filter and without using any filter.

The RSS variability over a time period of 0 to 30 is illustrated in Fig. 2. According to the results, the mean filter shows the most stable result compared with others. Results shown in Fig. 3 present comparison between the distance estimates based on different filtering methods and the actual value between node 1 and other nodes. It is provable that the distance estimation using RSS output from mean filter approaches well to the actual values. According to the evidences, $\bar{P}_{R_{ij}}$ resulted from the mean filter (5) will be used in the remaining steps of our proposed solution to estimate the distance.

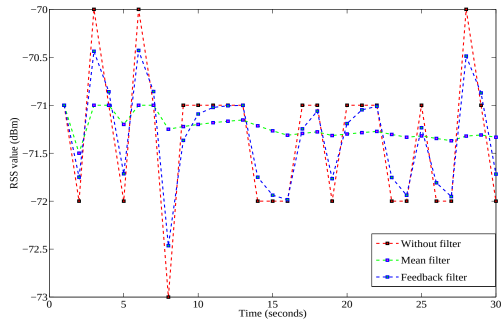


Figure 2: RSS variability over time.

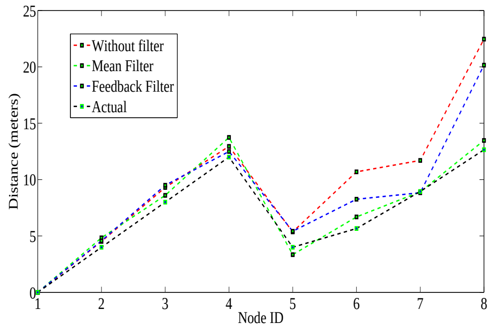


Figure 3: Distance estimates using RSS from different filters.

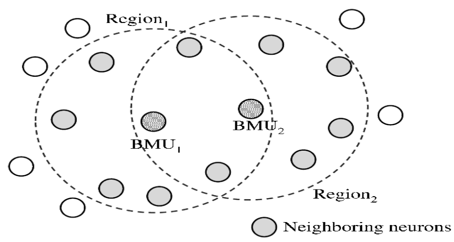


Figure 4: Distributed SOM network.

III. Proposed Hybrid RSS-SOM Localization Scheme

This section introduces our proposed hybrid RSS-SOM localization scheme which effectively exploits both RSS-based distance estimation and distributed SOM-based range free localization methods.

In our proposed scheme, the network itself becomes an SOM network in which each neuron is a node in that network. The weight of each neuron is associated with its initial estimated location. As illustrated in Fig. 4, each node becomes the Best-Matching-Unit (*BMU* or SOM-winner) at its local region (BMU_1 in $Region_1$, BMU_2 in $Region_2$ and so on). Neighboring neurons of *BMU* are determined by the communication range. Each *BMU* node updates only the weights of its neighbors. As well, *BMU* nodes also receive updates from other nodes when it becomes 1-hop neighbor of other *BMU* nodes. As an example, locations of the nodes within radio range of BMU_1 are updated by BMU_1 and BMU_1 itself also receives update from BMU_2 since it is the neighbor node of BMU_2 in $Region_2$. The nodes with known locations (anchors) do not update their positions.

There are two main stages in our proposed scheme, (a) initialization stage and (b) learning stage. Initial locations of the nodes

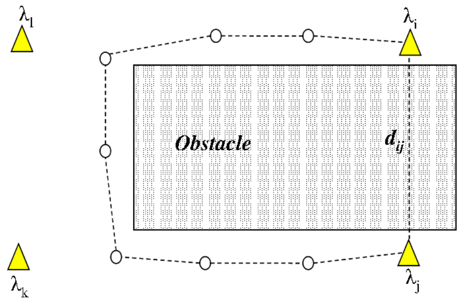


Figure 5: Topology with obstacles.

in the network are calculated in the initialization stage. Obstacle avoidance mechanism is incorporated in this stage. Updating location information takes place in the learning stage which is the core stage of the proposed scheme. Before going into detail of our scheme, let us formulate the mathematical notations used in this paper. A wireless ad hoc or sensor network is represented as an undirected connected graph where the vertices are nodes' locations and edges are the connectivity information (direct connection between neighbor nodes). The network is formed by *G* anchor nodes with known locations λ_i(i=1,2, ... ,G) and *N* nodes with unknown locations ω_i (i=1,2, ... ,*N*). The estimated locations of nodes are denoted as $\bar{\omega}_i$(i=1,2, ... ,*N*).

A. Initialization Stage

For the initialization stage, we apply the method similar to DV-HOP [13] to get the estimated locations. In the first step, each anchor node *i* broadcasts a beacon to be flooded throughout the network containing the anchors' locations with a hop-count value initialized to one. Each receiving node maintains the minimum hop-count value per anchor 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 anchor node.

In the second step, each anchor estimates an average size for one hop (hop distance) using the following equation,

$$H_i = \frac{\sum_{j\neq i} |\lambda_i - \lambda_j|}{\sum_{j\neq i} h_{ij}} \tag{8}$$

where h_{ij} is the hop count between two anchors *i* and *j*. In DV-HOP algorithm, unknown nodes have to use the hop distance value of nearby anchor to estimate distance to other anchor nodes. Then, lateration method is applied to estimate the location of the unknown node. However, these values are inaccurate with anisotropic networks where there is an irregular network shape or obstacle inside the network as illustrated in Fig. 5. According to the extensive simulations from [3], the average hop distance value is approximately $\frac{1}{\sqrt{2}}R$. Therefore, the possible number of hops between the two anchors *i* and *j* is $\frac{\sqrt{2}d_{ij}}{R}$ where *R* is the radio range. However, as shown in Fig. 5, if there is an obstacle between anchors *i* and *j*, the number of hops h_{ij} becomes larger, leading to inaccurate hop distance estimation in DV-HOP. In our work, each anchor node defines degree (D_{ij}) which is calculated using (9) to overcome this problem.

$$D_{ij} = \frac{\sqrt{2}(|\lambda_i - \lambda_j|)/R}{h_{ij}} \tag{9}$$

Smaller value of D_{ij} means there may be anisotropic areas located between anchor *i* and *j*. The nodes near anchor *i* will utilize these degrees to decide which two additional anchors have to be utilized for the lateration process (a minimum of 3 anchors are needed in 2D plane). Initial estimated locations of unknown nodes are obtained at the end of this step.

B. Learning Stage

There are four main phases in each learning stage which will be repeated in a total of *T* learning steps.

1) Phase 1: In the first phase, the nodes exchange location information so that each node has location information about its one hop neighbors with locations $\bar{\omega}_{ij}$ (*j*=1,2, ... ,N_i) where N_i is the number of nodes within node *i*'s communication range. The exchange packet contains the current learning step number, nodeID and the node's estimated location. Upon receiving of the location exchange packet, the nodes also measure the RSS values of the packets from each neighbor and keep them for further ranging based estimation process.

2) Phase 2: The second phase is the location update phase. Each node with location $\bar{\omega}_i$ becomes the SOM winner for each region. Based on classical SOM, it will update the weights of its neighboring nodes with the following formula,

$$\bar{\omega}_{ij}(m+1) = \bar{\omega}_{ij}(m) + \Delta(m) \tag{10}$$

where *m* is the current learning step. Δ(*m*) is calculated using (11).

$$\Delta(m) = \alpha(m)(\bar{\omega}_i(m) - \bar{\omega}_{ij}(m)) \tag{11}$$

where α(*m*) is the learning rate exponential decay function at iteration *m* as defined in (12).

$$\alpha(m) = exp(-\frac{m+1}{T}) \tag{12}$$

Updating by (10) means that the nodes will move towards the location determined by $\bar{\omega}_i$. If distance information from node *i* to *j* is available, it will be possible to draw node *j* towards the location determined by that distance information. Therefore, in our proposed scheme, we first utilize the ranging technique described in section II to get the distance information. Using a total of *m* RSS samples from phase 1, we first filter the RSS unreliability with the mean filter from (5) where *k*=*m* and then calculate d_{ij} using (7). Now we calculate the revising vector V_{ij} for all neighboring nodes *j* (1,2, ... ,N_i) that has the direction towards the location of d_{ij} away from node *i* using (13).

$$V_{ij} = \frac{d_{ij} - |\bar{\omega}_i - \bar{\omega}_{ij}|}{|\bar{\omega}_i - \bar{\omega}_{ij}|}(\bar{\omega}_i - \bar{\omega}_{ij}) \tag{13}$$

Then, the vector V_{ij} is used as a guidance to update the location of each neighbor node by changing (10) to (14).

$$\bar{\omega}_{ij}(m+1) = \bar{\omega}_{ij}(m) + (\Delta(m)(1-\beta)) - V_{ij}\beta \tag{14}$$

where β is the learning bias parameter calculated using

$$\beta = \begin{cases} 0 & : \quad m \leq \pi \\ 1 & : \quad m > \pi \end{cases} \tag{15}$$

where π is the learning threshold.

This threshold determines the steps to apply the proposed modification and the number of RSS samples. Before the current learning step *m* reaches the threshold, the topology is relatively converged by (10), and RSS measurement process in phase 1 and RSS-based distance estimation take place on each step. In the rest of the learning steps, the proposed modification is applied and d_{ij} from the learning step *m*=π will be utilized without any additional RSS measurement and RSS-based distance estimation processes to reduce computational costs since static network environment is considered which will not be changed within the localization process.

Table I: Simulation Parameters

Parameter	Value
Network area	10 x 10 $meter^2$
Radio range	2 *meter*
Learning threshold π	10
Total learning steps T	100

3) Phase 3: After calculating the newly estimated locations for all neighbors, node *i* with location $\bar{\omega}_i$ broadcasts a packet containing learning step number *m*, nodeID and a list of updated locations for its neighbors. Upon receiving this packet, each neighbor extracts its estimated location, as well, the node itself also receives the similar updates from its neighbors. Then, the node with location $\bar{\omega}_i$ calculates its newly estimated location by averaging its current location and the updates from its neighbors using (16) if it is not an anchor node.

$$\bar{\omega}_i = \frac{1}{N_i+1}[(\sum_{j=1}^{N_i}\bar{\omega}_{ji}) + \bar{\omega}_i] \qquad (16)$$

4) Phase 4: We utilize anchor information in this phase to adjust nodes' locations to approach to their absolute locations using (18).

$$\varphi_i = \frac{1}{G_i}\sum_{j=1}^{G_i} W(x)\frac{(\lambda_j - \bar{\omega}_i)}{|\lambda_j - \bar{\omega}_i|} \qquad (17)$$

$$\bar{\omega}_i = \bar{\omega}_i + \varphi_i \qquad (18)$$

$$W(x) = \begin{cases} -x^2 & : \quad (-1 \le x \le 0) \\ x^2 & : \quad (0 < x \le 1) \\ 1 & : \quad (x > 1) \end{cases} \qquad (19)$$

$$x = \frac{|\lambda_j - \bar{\omega}_i|}{h_{ji}R(1/\sqrt{2})} - 1 \qquad (20)$$

where h_{ji} is the hop count from anchor *j* to node *i* and G_i is the total number of anchors. All these phases are done in one learning step and all the nodes repeat for T learning steps to get desired location accuracy. The weights obtained from the final learning step are the estimated locations of the nodes.

IV. Simulation Evaluations

To evaluate the performance of proposed scheme, extensive simulations have been carried out on different topologies, anchor utilization, node density and connectivity level. The following mean error value is used as a localization accuracy evaluation function.

$$err = \sqrt{\frac{1}{N}\sum_{i=1}^{N}|\omega_i - \bar{\omega}_i|^2} \qquad (21)$$

where N is the total number of nodes with unknown locations. All the simulations have been conducted in MATLAB simulation environment. The common parameters used in simulations are presented in TABLE. I.

For the ranging based distance estimation, RSS values are calculated from each neighbor according to (2) where d_0 was set to 1, and n_i to 2.5 and the shadow fading X_σ is simulated as a Gaussian random variable with zero mean and standard deviation of 4, assuming propagation model for indoor environment with Non Line of Sight connection. To apply our proposed scheme in real fields, values of n_i and standard deviation can be changed to characterize the propagation channel. We assume all the sensor nodes have the same transmit power and radio range.

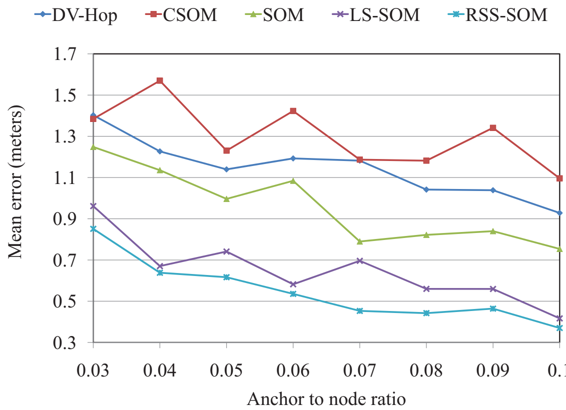


Figure 6: Performance by number of anchors.

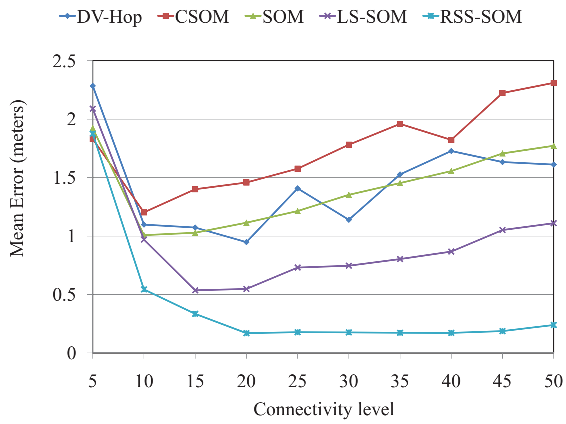


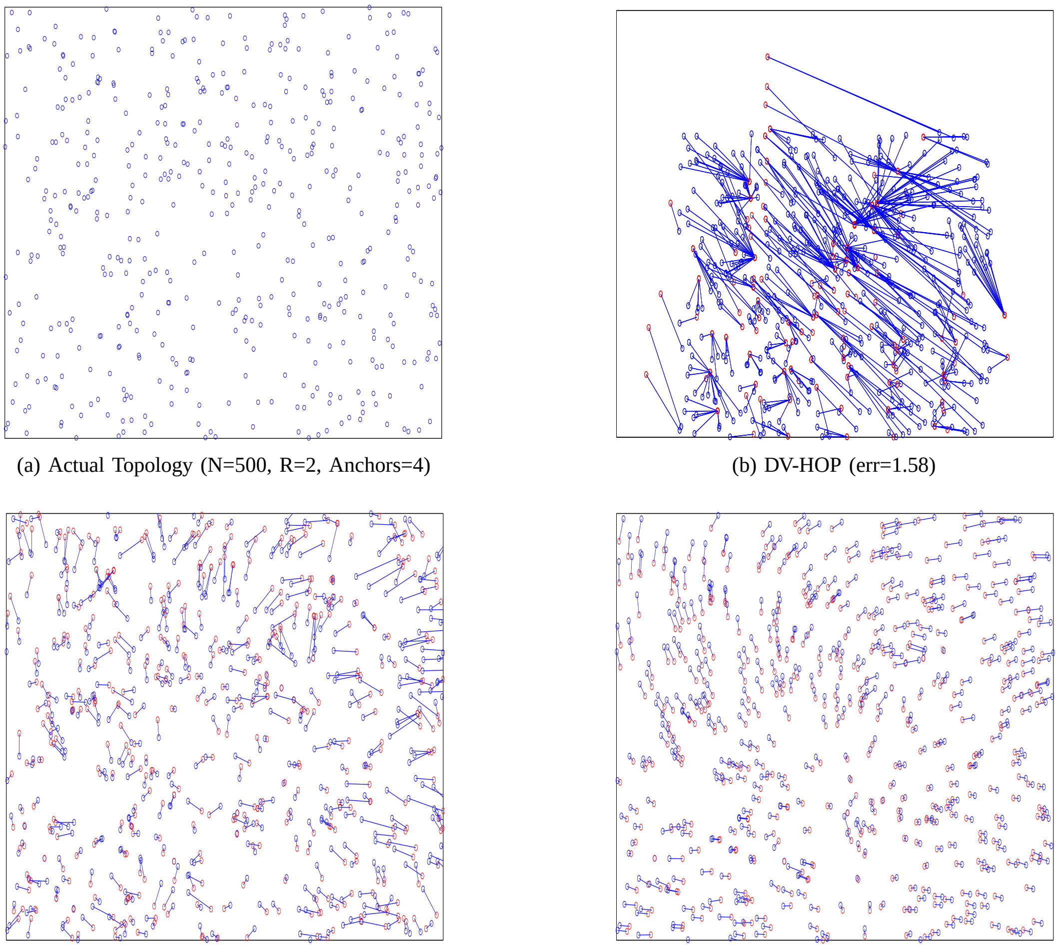
Figure 7: Performance by node density.

A. Localization Performance for Randomly Distributed Networks

At first, we conduct the experiments on a randomly distributed network with 100 nodes to evaluate the performance of our proposed method while varying connectivity level and number of anchors utilized. Here the connectivity level represents average number of neighbors per node. To ease the performance comparison, we call the previous works in [3] and [4] as SOM and LS-SOM respectively, the method by G.Giorgetti et al. [14] as CSOM and our proposed method as RSS-SOM. Mean errors of our proposed scheme for different number of anchors are compared with that of the SOM-based localization approaches and the DV-HOP approach. As illustrated in Fig. 6, RSS-SOM scheme shows the best result among other schemes even in the case of the minimum number of anchor utilization.

Mean location errors of different schemes on various connectivity levels are shown in Fig. 7. Results indicate that our proposed RSS-SOM scheme achieves very good accuracy over the other schemes from sparse to dense networks.

Topology generations for large scale networks are illustrated in Fig. 8 where 500 nodes are randomly distributed with 0.8 % anchor utilization. The blue circle and the red circle represent the actual location and the estimated location respectively, and the connecting line between them shows the localization error. DV-HOP gets higher error due to the hop distance estimation error. Although LS-SOM approach achieves better accuracy than DV-HOP, RSS-SOM gets the best location accuracy among them.



(a) Actual Topology (N=500, R=2, Anchors=4)

(b) DV-HOP (err=1.58)

(c) LS-SOM (err=0.34)

(d) RSS-SOM (err=0.22)

Figure 8: Topology regeneration for high node density.

Additionally, to make the comparison with hybrid schemes, RSS-DVHOP and SRSSQ, which use both RSS ranging and range free localization, a random network environment of 200 nodes and 5 % anchor utilization with the radio range of 15 has been constructed in an 100x100 $meter^2$ area as in [9]. According to the results in Fig. 9, our RSS-SOM scheme shows 68 % and 30 % performance improvement over RSS-DVHOP and SRSSQ respectively.

B. Topology Generation for Anisotropic Networks

In this work, we also evaluate our proposed scheme on networks having irregular shapes or obstacles. Fig. 10 shows the localization performance for the network with 100 nodes and 4 anchors distributed in a C-shape area. Here, the red dots represent the placement of anchor nodes and the lines represent the connectivity among the nodes. Mean errors for the network with 100 nodes and 4 anchors distributed in an area with three big obstacles inside the topology are described in Fig. 11. Since LS-SOM scheme also includes solution for obstacle impact, it showed preferable location accuracy than CSOM. However, due to the better accuracy of ranging based approach, our proposed hybrid scheme still achieves around 20 % and 50 % improvement over the LS-SOM for each topology respectively.

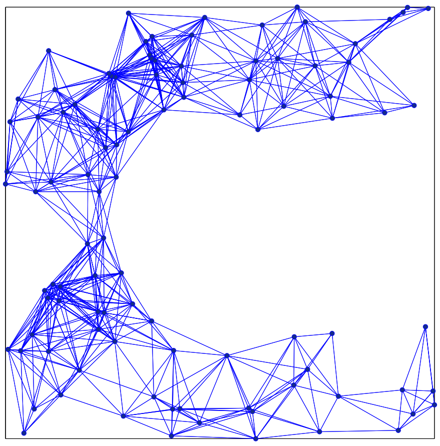
Mean error through each SOM learning step of RSS-SOM scheme is presented in Fig. 12. The RSS-SOM scheme requires only 20 to 30 learning steps to achieve stable result. Comparing to thousands of learning steps in classical SOM and 30 to 40 steps in LS-SOM,

Figure 9: Performance comparison with hybrid schemes.

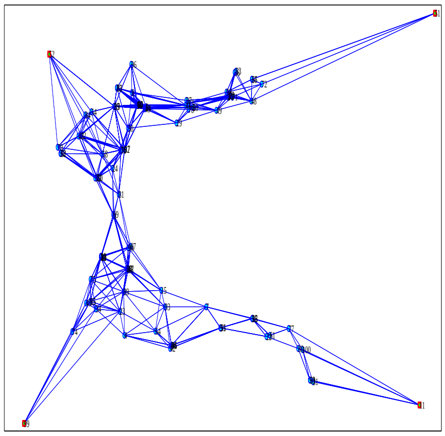
our proposed scheme reduces communication and computational overheads.

V. Conclusion

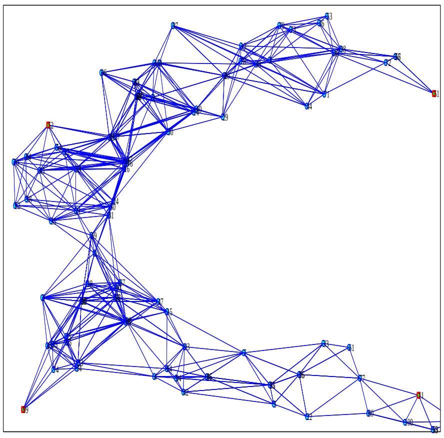
In this work, we have proposed a new hybrid RSS-SOM localization scheme which effectively exploits benefits of the RSS ranging based approach and the distributed SOM-based localization



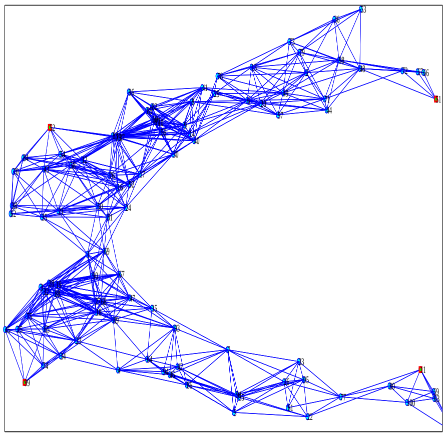
(a) Actual Topology (N=100, R=2, Anchors=4)



(b) CSOM (err=1.5)



(c) LS-SOM (err=1.1)



(d) RSS-SOM (err=0.81)

Figure 10: Topology generation for the C-shape network.

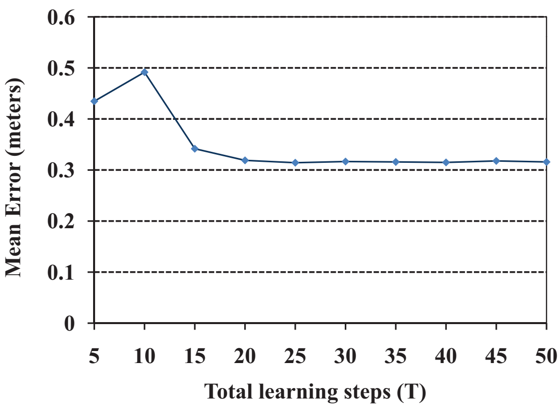


Figure 12: Average error per total learning steps of RSS-SOM scheme.

approach. Location accuracy of SOM algorithm has been improved by integrating a more precise distance estimation method based on RSS measurements. Factors on RSS variance smoothing and obstacle filtering have also been considered in our proposed scheme. According to the results, our proposed hybrid scheme works well not only on random networks but also on networks with irregular shapes. As well, it depicts the highest localization accuracy among other schemes even in the case of low anchor utilization and also for sparse to dense node density. Likewise, the proposed hybrid RSS-SOM localization scheme has reduced the computational and communication cost since it needs only a few number of learning steps to get stable localization accuracy. Achieving tradeoff between cost, power and accuracy is the main benefit of our research. Limitation on this work is that it works well only on the static network environment and mobility is not considered. Future condiderations of current work are to consider a more precise and effective RSS filtering method, to give location accuracy on both static and mobile networks and to deploy it in real systems.

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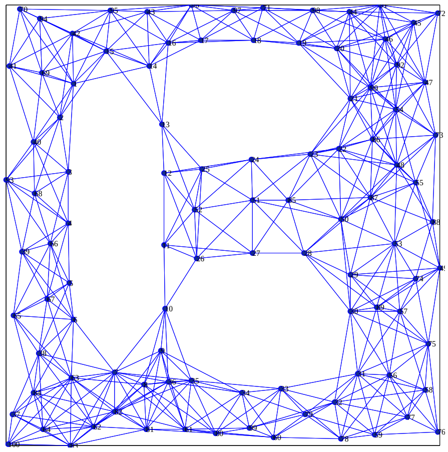
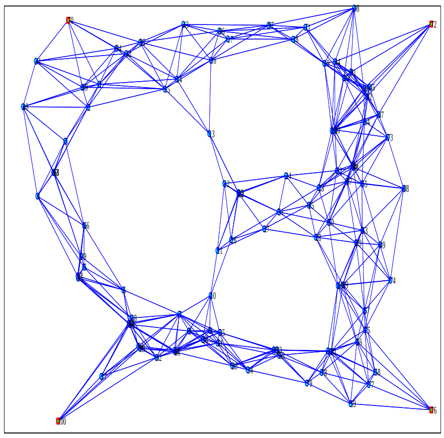
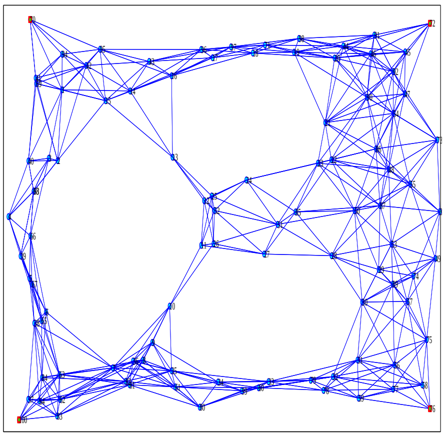


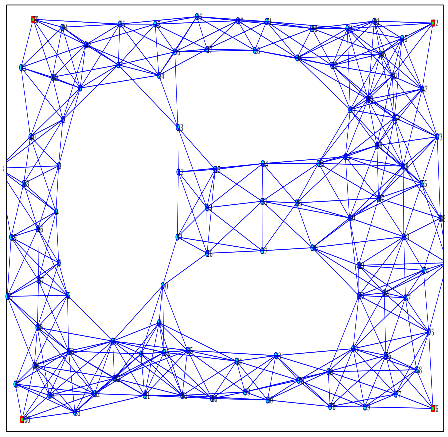
(a) Actual Topology (N=100, R=2, Anchors=4)



(b) CSOM (err=0.78)



(c) LS-SOM (err=0.46)



(d) RSS-SOM (err=0.24)

Figure 11: Topology regeneration for the network having obstacles.

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