Wireless Ad Hoc Network Positioning Algorithm based on Self-Organizing Maps and Received Signal Strength

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Abstract Positioning or localization of wireless ad hoc networks has gained much research attentions for several years. This paper proposes a hybrid positioning algorithm which exploits Received Signal Strength (RSS)-based ranging and Self Organizing Maps (SOM)-based range free localization methods to obtain the tradeoff 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 number of learning steps. Method on RSS uncertainty reduction is also incorporated in the proposed hybrid RSS-SOM algorithm. Results from extensive simulations prove that the hybrid RSS-SOM algorithm outperforms several existing positioning algorithms for all node density, anchor utilization and the number of learning steps.

Keywords RSS, SOM, Positioning

positioning accuracy while reducing cost, power and anchor utilization. As motivations to our previous works, our proposed algorithm modifies existing SOM-based approaches by applying RSS-based distance information in the learning steps of location update process. To smooth out the RSS instability, a mean filter has been utilized. Extensive simulations have been carried out to evaluate the performance of the RSS-SOM algorithm and the results show a high degree of accuracy compared with other existing works. The rest of the paper is organized as follows: section 2 describes detail explanation on the hybrid RSS-SOM algorithm. Section 3 provides simulation results and performance evaluations. Finally in section 4, we summarize our results and discuss the future works.

II. PROPOSED WIRELESS AD HOC NETWORK POSITIONING ALGORITHM

This section introduces the proposed hybrid RSS-SOM positioning algorithm which effectively exploits both RSS-based distance estimation and distributed SOM-based range free positioning methods to bridge the gap between low consumption of power and cost, and high accuracy. There are two main stages in the RSS-SOM algorithm: (i) initialization stage and (ii) learning stage. Before going into detail of the algorithm, let us formulate 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 $\overline{\omega}_i$ (i=1,2,...,N).

A. Initialization Stage

For the initialization stage, we apply the method similar to DV-HOP [9] to get the initial estimated locations. In DV-HOP, unknown nodes have to use the average hop distance value (H_i) of nearby anchor i which is calculated using (1) to estimate distance to other anchor nodes.

$$H_i = \sum_{j \neq i} \left| \lambda_i - \lambda_j \right| / \sum_{j \neq i} h_{ij} \quad (1)$$

where h_{ij} is the hop count between two anchors i and j. After obtaining the distance between unknown node and other anchors, lateration method is applied to estimate the location of the unknown node. Initial estimated locations of unknown nodes are obtained at the end of this step.

B. Learning Stage

This is the core stage of the proposed algorithm which applies both RSS-based distance information and distributed SOM-based positioning algorithm to estimate the location of unknown nodes. There are four main phases in the learning stage which will be repeated in a total of T learning steps.

1) Phase 1: Location exchange phase

In the first phase, the nodes exchange their location information so that each node has location information about its one hop neighbors $\overline{\omega}_{ij}$ (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 (m), nodeID and the node's estimated location. Upon receiving of the location exchange packet, the nodes measure the RSS values of the packets from each neighbor and keep them for further ranging based estimation process.

2) Phase 2: Distance estimation using Received Signal Strength (RSS)

To estimate the distance between the two communicating nodes, we adopt the log-normal shadow model [10] which is a more general propagation model suitable for both indoor and outdoor environments. The signal strength of the received packet (RSS) can be related to the distance between the two nodes by the following expression:

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

where d_{ij} is the distance between node i and j, 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

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

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

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

However, estimating the distance from a single RSS measurement is erroneous due to RSS variability. Two common filters to smooth out it are simple averaging (mean) filter and feedback filter. The mean filter simply calculates the average of RSS values ($\overline{RSS}_{ij}$) from the first to current learning step m (t=1 to m) in which we can assume that the distance and the environment between the two communicating nodes do not change significantly.

$$\overline{RSS}_{ij} = \frac{1}{m}\sum_{t=1}^{m} RSS_{ij}\ (\mathrm{t}) \tag{5}$$

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

$$\overline{RSS}_{ij} = \alpha RSS_{ij}(t) + (1-\alpha) RSS_{ij}(t-1) \tag{6}$$

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

$$d_{ij} = 10^{\frac{P_{ref} - \overline{RSS}_{ij} + X_\sigma}{10n_i}} \tag{7}$$

The RSS variability over a time period of 0 to 30 is illustrated in Fig.1. According to the results, the mean filter shows the most stable result compared with others. Results shown in Fig.2 present the comparison between the distance estimates based on different filtering methods and the actual value. It is provable that the distance estimation using RSS output from mean filter approaches well to the actual values. According to the evidences, using a total of m RSS samples, we filter the RSS unreliability with the mean filter (5) and then calculate d_{ij} using (7).

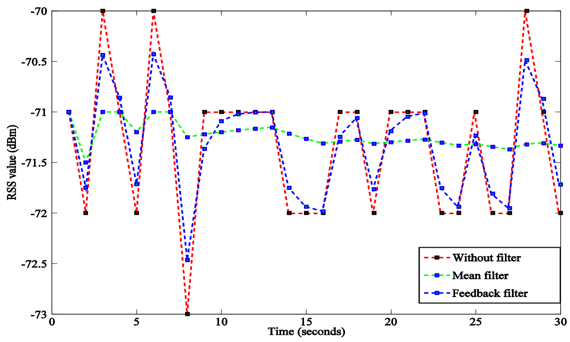


Fig.1. RSS variability over time.

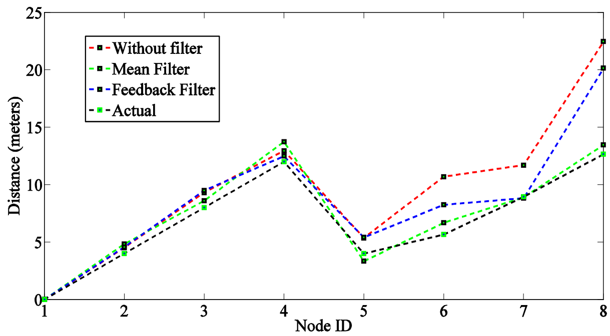


Fig.2. Distance estimates using RSS from different filters.

3) Location update phase

The third phase is the location update phase. Each node with location ϖ_i becomes the SOM winner for each region. Based on classical SOM, it will update the weights of its neighboring nodes with location ϖ_{ij} using the following formula,

$$\varpi_{ij}(m+1) = \varpi_{ij}(m) + \Delta(m) \tag{8}$$

where m is the current learning step. $\Delta(m)$ is calculated using (9).

$$\Delta(m) = \alpha(m)\left(\varpi_i(m) - \varpi_{ij}(m)\right) \tag{9}$$

where $\alpha(m)$ is the learning rate exponential decay function at iteration m as defined in (10)

$$\alpha(m) = \exp(-\tfrac{m+1}{T}) \ . \quad (10)$$

Updating by (8) means that the nodes will move towards the location determined by $\overline{\omega}_i$. 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. Therefore, we utilize d_{ij} resulted from the second phase and calculate the revising vector V_{ij} for all neighboring nodes j $(1,2, \ldots ,N_i)$ that has the direction towards the location of dij away from node i using (11).

$$V_{ij} = \frac{d_{ij} - |\overline{\omega}_i - \overline{\omega}_{ij}|}{|\overline{\omega}_i - \overline{\omega}_{ij}|}(\overline{\omega}_i - \overline{\omega}_{ij}) \quad (11)$$

Then, V_{ij} is used as a guidance to update the location of each neighbor by changing (8) to (12).

$$\overline{\omega}_{ij}(m+1) = \overline{\omega}_{ij}(m) + \big(\Delta(m)(1-\beta)\big) - V_{ij}\,\beta \quad (12)$$

where β is the learning bias parameter:

$$\beta = \begin{cases} 0 \; if \; m \le \pi \\ 1 \; if \; m > \pi \end{cases} \quad (13)$$

where π is the learning threshold. This threshold determines the steps to apply the proposed modification and the number of RSS samples. Before m reaches the threshold, the topology is relatively converged by (8) and RSS measurement process in the first phase takes 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 process and the distance estimation phase to reduce computational costs since static network environment is considered which will not be changed within the positioning process.

After calculating the location updates for all neighbors, node i with location $\overline{\omega}_i$ broadcasts a packet containing current learning step number (m), nodeID and a list of updated locations for its neighbors. Upon receiving of 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 $\overline{\omega}_i$ calculates its newly estimated location by averaging its current location and the updates from its neighbors using (14) if it is not an anchor node.

$$\overline{\omega}_i = \frac{1}{N_i+1}\left[\left(\sum_{j=1}^{N_i} \overline{\omega}_{ji}\right) + \overline{\omega}_i\right] \quad (14)$$

4) Anchor information utilization phase

As in our previous works, we utilize known information of anchors in this phase to adjust nodes' locations to approach to their absolute locations based on equation (15).

$$\overline{\omega}_i = \overline{\omega}_i + \varphi_i \quad (15)$$

where $\varphi_i = \frac{1}{G_i}\sum_{j=1}^{G_i}, \quad W(x)\frac{(\lambda_j - \overline{\omega}_i)}{|\lambda_j - \overline{\omega}_i|}$, $W(x) = \begin{cases} -x^2 & (-1 \le x \le 0) \\ x^2 & (0 < x \le 1) \\ 1 & (x > 1) \end{cases}$ $and\ x = \frac{|\lambda_j - \overline{\omega}_i|}{h_{ji}\ R\theta_{ij}} - 1.$ (16)

h_{ji} is the number of hops from anchor j to node i, θ_{ij} is the ratio of the hop distance to radio range R and G_i is the total number of anchor nodes. 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.

III. SIMULATION EVALUATIONS

To evaluate the performance of the proposed algorithm, extensive simulations have been carried out for small to large scale networks, differing anchor utilization, node density and connectivity level. The following mean error value is used as a localization accuracy evaluation function.

$$err = \sqrt{\frac{1}{N}\sum_{i=1}^{N} |\omega_i - \overline{\omega}_i|^2} \quad (19)$$

where N is the total number of nodes with unknown locations. All the simulations have been conducted in MATLAB simulation environment.

For the ranging based distance estimation, RSS values are calculated from each neighbor according to (3), setting 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 algorithm in real fields, values of n_i and standard deviation can be changed to characterize the propagation channel. We assume all the nodes have the same transmit power and radio range R. Learning threshold π of 10 and total learning steps T of 100 have been used in our simulations.

A. Performance for Small Scale Networks

At first, we conduct experiments on a small scale network of 100 nodes distributed randomly in a 10x10 meter^2 area while varying connectivity level and number of anchors utilized. The connectivity level represents average number of neighbors per node. Here, we use the radio range of 2 meter. To ease the performance comparison, we call our previous works in [3] and [4] as SOM and LS-SOM respectively, and the method by [11] as CSOM.

Fig.3 illustrates the performance comparison of f RSS-SOM with other algorithms for different number of anchor utilization. RSS-SOM shows the best result among other algorithms even in the case of the minimum number of anchor utilization. Noticeable localization accuracy has been achieved with 10% anchor utilization.

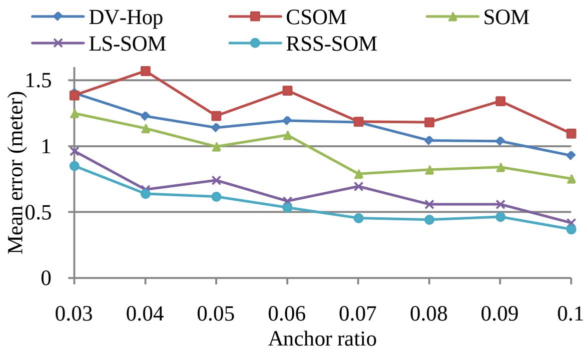


Fig.3. Performance by number of anchors.

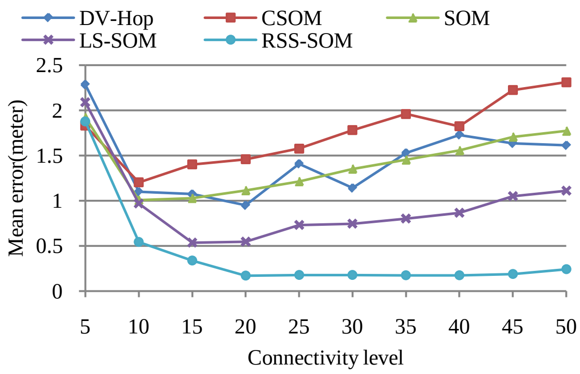


Fig.4. Performance by connectivity level.

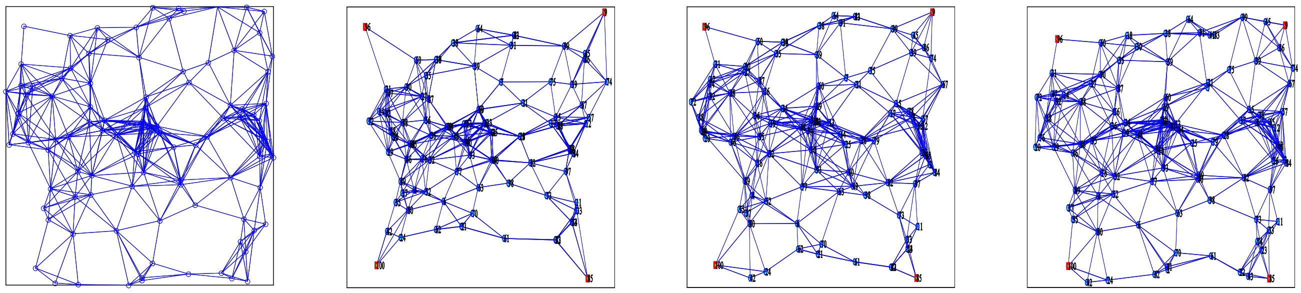
Mean location errors of different algorithms on various connectivity levels are shown in Fig.4. Results indicate that our proposed RSS-SOM algorithm achieves very good accuracy over the other algorithms from sparse to dense networks. Fig.5. illustrates performance comparison of topology regeneration for a random network with 100 nodes using 4 anchors. RSS-SOM shows that its performance is superior to other algorithms.

B. Performance for Large Scale Networks

Topology generations for large scale networks are illustrated in Fig. 6 where 500 nodes are randomly distributed with 0.8 % anchor utilization. Symbols 'o' and '*' represent the actual location and estimated location respectively, and the connecting line between them shows the positioning 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.

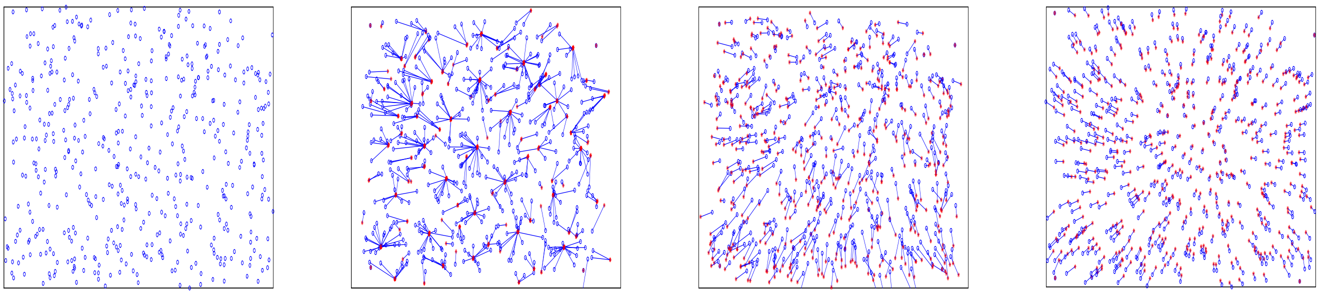
Localization accuracy over different values of radio range has been presented in Fig.7. Increasing the radio range dramatically reduces the localization accuracy of compared algorithms, except that our proposed RSS-SOM shows mostly stable results and the highest accuracy.

Additionally, we conduct another experiment on a random network of 200 nodes, 5 % anchor utilization and the radio range of 15 meter to make the comparison with hybrid schemes, RSS-DVHOP and SRSSQ. According to the results in Fig. 8, our RSS-SOM algorithm shows 68 % and 30 % performance improvement over RSS-DVHOP and SRSSQ respectively.



(a) Actual Topology (b)CSOM (err=0.9224) (c)LS-SOM (err=0.39) (d) RSS-SOM (err=0.28)

Fig.5.Topology regeneration of small scale networks.



(a) Actual Topology (b)DV-HOP (err=0.7433) (c)LS-SOM (err=0.4964) (d) RSS-SOM (err=0.23)

Fig.6. Topology regeneration for large scale networks.

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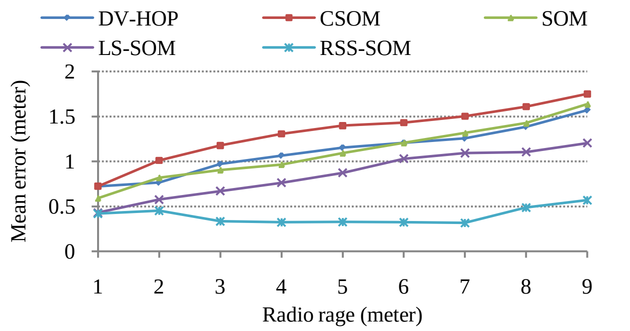

Fig.7. Performance by different values of radio range.

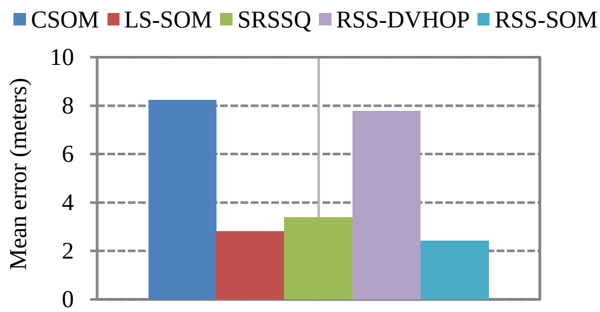

Fig.8. Performance comparison with hybrid schemes.

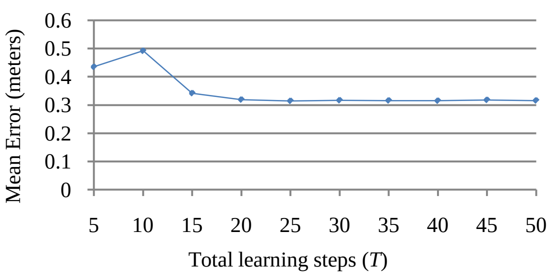

Fig.9. Mean errors per total learning steps.

Mean error through each SOM learning step of RSS-SOM scheme is presented in Fig. 9. 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, proposed RSS-SOM reduces communication and computation overheads.

IV. CONCLUSIONS

In this work, we have proposed a new hybrid RSS-SOM positioning algorithm which effectively exploits the benefits of both RSS ranging and SOM-based localization approaches. Location accuracy of

SOM algorithm has been improved by integrating a more precise distance estimation method based on RSS measurements. Factor on RSS variance smoothing has also been considered in the proposed algorithm. According to the results, our proposed hybrid algorithm works well on both small to large scale networks. As well, it depicts the highest localization accuracy among other algorithms even in the case of low anchor utilization and also for sparse to dense node density. Likewise, the proposed hybrid RSS-SOM algorithm 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 work will be to extend current work to give location accuracy on both static and mobile networks and to deploy it in real systems.

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