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A GPS-free Wireless Mesh Network Localization Approach

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Abstract

Wireless Mesh Networks (WMN) is a new type of wireless access network that combines the advantages of Wireless Local Area Networks (WLAN) with those of Mobile Ad hoc networks (MANET). The localization of mobile nodes in WMN has not been paid much attention as of yet in comparison with that of WLAN and MANET. As an essential component of user mobility support, localization in WMN should be more accurate in order to meet the need of mobile users in WMN. In this paper, we propose a Ring Overlapping based Localization algorithm (ROL) that is based on Subtle Partial Range Aware (SPRA) distance measurement method. The experiments show that our new algorithms receive better results than existing methods and can reduce localization error within 3 meters in buildings.

1. Introduction

Wireless Mesh Networks (WMN) [1] is a new type of wireless access network that combine the advantages of Wireless Local Area Networks (WLANs) with those of Mobile Ad hoc Networks (MANETs). The localization of mobile nodes in WMN has not yet been paid much attention as has localization in WLANs and MANETs. Note that both the features of auto-configuration in WMN and some research, such as geographical routing, needs to be supported by a localization algorithm. In addition, because more and more applications in WMN are emerging and some mobile nodes take WMN as a wireless access network, the requirement of providing location based services will extend. So, the importance of localization algorithms in WMN will be enhanced in the near future.

In this paper, we distinguish two kinds of mesh networks: (a) client-based mesh networks, wherein end-devices such as PDAs, laptops, called Mesh Client or Mobile node, participate in packet forwarding and (b) Infrastructure-based wireless mesh networks (IWMN), wherein end-devices (user) do not participate in the packet relay and the multi-radio relay nodes (called Mesh Router or Backbone node) compose the network infrastructure illustrated in Figure 1. This paper primarily focuses on previous kind.

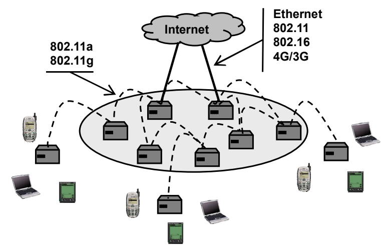

Figure 1 **Infrastructure-based wireless mesh**

However, most of the existing localization algorithms are based on MANETs or WLANs, which cannot utilize WMN's advantages effectively. Moreover, since there are so many differences among these wireless network architectures, algorithms that are developed for MANETs and WLANs may not work well in WMN. Therefore, a new WMN based localization method is required.

In this paper, we propose a novel approach of localization, which includes two parts: Subtle Partial Range Aware (SPRA) method and Ring Overlapping based Localization algorithm (ROL). The former mainly focuses on mapping the signal power received by mobile node to corresponding distance more precisely, and the latter utilizes this distance information to complete its localization procedure within WMN infrastructure.

The rest of this paper is organized as follows: Section II gives an overview of related works. Section III introduces the SPRA method and section IV describes ROL in detail. Section V carries out our experiments and evaluation. Finally in section VI, we draw a conclusion and state possible future works.

2. Related work

It is always recommended that people use GPS for

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location based information. GPS related methods or algorithms work well in networks in which topology is relatively static. But for MANETs or WMNs, problems cannot be exclusively attributed to GPS. Since nodes in these situations are often portable and small, the location information of these nodes through means of a GPS based piece of equipment on these clients seems too costly. Also, overhead and resource limitations have to be taken into consideration. But that does not mean GPS can not be used in a WMN localization algorithm. In fact, GPS facilitated location information is increasingly likely to be used on anchor nodes or backbone nodes in WMN. In this paper, we assume there are always several backbone nodes that retain precise location information of themselves, despite whether such information is acquired through GPS. What we mainly focus in this paper is to utilize what we have to localize all the mobile nodes or client nodes. And in this field, most localization methods related are GPS-free.

2.1. Distance measurement methods

Distance measurement methods are the basis of wireless node localization. An accurate and effective method can not only provide critical distance information precisely and chronologically, but also prevent resources from being over exploited. There are mainly three kinds of distance measurement methods, which are respectively based on signal transmission time, signal transmission route and transmission signal power (Received Signal Strength Identifier, RSSI).

It is simple to understand the pivotal concept in the first of the aforementioned solution. If wireless signal transmission speed is c, and time between signal sent and received is t, the distance between sender and receiver is c*t. Time of arrival (TOA) [2] belongs to this kind of method, which is used in cellular networks. The major disadvantage of this method lies in that it needs time synchronization between each sender and receiver. Additionally, the speed of radio frequency is too difficult to be measured accurately. Both two systems in [3] and [4] using radio frequency signal to implement time synchronization. Supersonic signals are used to measure distance. Since the approach in [3] signal's speed is much faster than the that in [4], and that radio frequency's transmission time can be neglected within a short range, the time difference can thus be used as the signal transmission time. In addition, supersonic has always had a relatively low transmission speed, and can therefore be used in short range measurement. However, this requires all nodes in WMN to be equipped with both supersonic sender and receivers, which is fiscally implausible.

The signal transmission route based methods are more frequently used in systems which do not require high accuracy. For example, DV-hop algorithm in APS system [5] is an implementation of this kind. The DV-hop algorithm does not measure distance between nodes directly. Rather, in its localization system, there are always some landmark nodes that know their own location; other nodes get average hop distance with the help of hop count and distance from landmark nodes. After computing distances from all landmark nodes, a node can thus process its own location. Methods like DV-hop do not have a high accuracy because they can only be used in multi-hop networks where nodes are regularly distributed. When it comes to measuring distances between neighbors this method is rarely a practical one.

The final category of distance measurement to be discussed is based on RSSI. Most of the distance measurement problems in this category of methods have a defined solution in the transmission model and correspondent formulas. However, we can hardly find a transmission model that suits all actual environments. Furthermore, because of the mapping rules of transmission models that a single RSSI value maps to a set of distance value instead of a single one, accuracy is also to be questioned. The PRA method [6] is based on the idea above. PRA does not depend on wireless transmission models, rather, it cuts its transmission range R into S segments, and assigns each segment a definite value of $j*R/S$ $(0<j<S)$. Then it sorts all nodes according to the level of received signal strength. Finally, after choosing different mapping models, it assigns different distance value to each of its neighbors. Since PRA does not utilize RSSI as its measurement basis, it has a virtually predetermined and incorrigibly high level of measurement error.

2.2. WLAN localization methods

Localization algorithms in WLAN can be categorized into four different kinds: experiment algorithms, statistic algorithms, signal transmission based algorithms, and hybrid algorithms.

RADAR method [12] is the typical experiment algorithm. The means by which this method works is similar to that of fingerprint matching. In RADAR system, 3 APs are set in each floor. A system contains two main stages: the offline stage and the online stage. In offline stage, a mobile node measures the signal strength from each AP while continuously changing location. The resulting data is then stored into a database. At the online stage, a user can get its location simply by measuring signal strength from APs and then searching the database for matching results. RADAR system's measurement error is about 3 meters. Its main drawback is in need of a large amount of offline works in advance. Additionally, result data can not be reused in a new environment.

Algorithms in [13] and [14] are both statistic based. In order to get the relationship between signal strength and distance, it requires data or history results as a training set for the machine to "learn" with statistic models. These methods do not need so many offline works, and statistics based methods can support categorization as well. But statistic methods need data and history result as a training set, and accuracy problems should also be considered.

A common feature of the above mentioned algorithms is the need of much offline work, be it offline measurement or offline machine learning. It significantly prolongs the configuration time of system and makes them better fit stable networks. But for temporary networks or system fault, these methods can not handle well.

Comparing experimental methods and statistical methods, it can be seen that signal transmission based methods do not need so many offline works. Its principle is to measure signal strength from multiple APs and use multilateration to localize a node, which is mainly used in GPS positioning. This is a classical positioning method. However, wireless signal transmission regularity is hard to summarize, especially in an indoor environment,. Thus, measurements of signal strength will result in a high error rate. It is therefore imprudent to perform polygon calculations directly in this situation, since accuracy can not be ensured. But this method has zero-configuration, the least number of offline works required and other potential advantages which other methods cannot match. It is clear that there is much more potential of this method. And many works are focusing on it because of this.

2.3. MANETs localization methods

In mobile ad hoc networks, besides the needs of location service and localization algorithm, some routing protocols and applications such as LAR also need localization support. Therefore, localization is always an essential topic in ad hoc networks.

The SPA (Self Positioning Algorithm) in [7] is the earliest GPS-free ad hoc positioning algorithm. In their algorithms, each node constructs a local coordinate system, which includes all its one hop neighbors. The node stands at the coordinate origin and chooses two of its neighbors to determine the x-axis and y-axis. Then it computes other neighbors' positions using general geometric methods. Two adjacent coordinates, whose origins are neighbors, can then merge into a larger coordinate with the help of a common node of both sides. In order to absorb all nodes into a single coordination, SPA defines Location Reference Group (LRG) nodes, and forces any other coordinates to be absorbed into LRG coordinates. The SPA algorithm has both high accuracy and high coverage but these advantages exist at the cost of large amounts of calculation (big overhead).

The LPS (Local Positioning System), proposed in [8], is application-specific. It is essentially a synthesis of the localization algorithm and the Trajectory Based Forwarding (TBF). In LPS, only data sources construct local coordinate system, subsequently providing localization service for nearby nodes. When a TBF is determined, we can choose any one of them as the origin of the coordinate. While LPS uses the coordination calculation methods in SPA, the only different is that it focus on TBF, which reduces the number of attendant nodes

The CBA (Cluster Based Algorithm) in [9] focuses on solving the problem of overheads in SPA by dividing nodes into master nodes and slave nodes. Master nodes are chosen randomly. All one hop neighbors of one master node are its slave nodes, meaning that that there are at least two hops between any master nodes. Each master node chooses itself as the origin and constructs its own local coordinate which is similar to SPA. Experiments show that the overhead of CBA is obviously lower than SPA.

The BGFL (Backbone-based GPS Free Localization) algorithm [10] points out the potential problem in CBA. Because master nodes are not directly connected, it is not robust enough to use quadrilateral consisting of two common nodes and two origins. When it comes to coordinates emerging, this potential problem may incur flapping ambiguity. Works in [10] and [11] verify this analysis through NS-2 simulation. BGFL primarily focuses on reducing overhead of SPA. BGFL first construct a backbone network through messages, which is different from CBA. Since nodes in backbone network are connected, BGFL can use the coordinate emerge method in SPA while prevent the errors in CBA. BGFL's overhead is lower than SPA and its accuracy is almost the same as SPA.

To synopsize, since client nodes in ad hoc network are mostly laptops or PDAs, it is unwise to use GPS based localization algorithm to provide location service. Approaches above provide a basic view of solutions in this field.

3. Subtle Partial Range Aware method

PRA method does not consider definite values of signal power, only mapping segments according to order of signal power. It surely will result in high measurement errors. In order to overcome this drawback, we propose Subtle Partial Range Aware (SPRA) method in this paper, which is based on more subtle quantitative approach.

Wireless signal transmission character can be described by mathematic model. We can build a mapping relationship between signal power and distance. However, signal will be influenced in practical scenarios. As a result, scattering, diffraction, reflection and other unexpected situation may occur. Therefore, we can hardly use only one transmission model to describe this mapping relationship precisely in a particular situation. Moreover, the signal power is measured in 1dBW in accuracy at most cases, which also prevent mapping signal power to a definite distance value. For example, in FreeSpace model, -77dBW have equal possibility of mapping 93m to 103m, and -82dBW can map to any distance between 165m to 184m. In the model of TwoRayGround, -77dBW can map to 90m to 94m, and -82dBW can map to 120m to 129m. So we can see that, if we map a certain signal strength value to a single distance value, it will bring at least 10 meters error in measurement, which can not be tolerated. If we consider errors of measuring signal, we will get even more trouble.

SPRA in this paper combines PRA method and signal measurement methods. In SPRA we do not map a single signal strength value to values or sets. We map sets to sets. Through this kind of set to set mapping, we can avoid error incurred by single value mapping, and also reduces measurement errors brought by measurement accuracy.

Mapping principle is directly related to transmission model. Before determining mapping rules, we should firstly get signal strength value at different distance within transmission range. Then we can settle down mapping rules according to the accuracy we want. It is recommended that we use integer as measurement unit. In some environments, we can not determine what transmission model should be used. At this time, we should use experiment method to collect necessary data for building the mapping rules. The unit of signal strength is usually dBW or dBm. In theoretical models, signal power is always measured by Watt. For convenience, we need to transform Watt to one of the units above. The formula is given in Formula 1.

$$P(dBW) = 10\log\left(\frac{P(W)}{1(W)}\right)$$
$$P(dBm) = 10\log\left(\frac{P(W)}{0.001(W)}\right) \quad (1)$$

Signal power values in dBW or dBm are linear relative with distance values. We can utilize this point to make sets better divided. Regarding set division, it is hard to carry out a quantitative rule for all transmission models. But there are principles for this work. If based on the changes of signal power strength, we can divide signal strength into sets in equal size, whose maximum value and minimum value map to the biggest and smallest value of distance respectively. Also we can choose the distance value as standard to divide signal power sets. It is not a must to divide sets into equal size. We can adjust specific set size according to the change trends of the function. It is recommended that sets that values changes fast have a smaller size and sets that values changes relatively slow have a bigger size. Size of signal power sets should between 5dBW to 10dBW. When it comes to distance, the set size should be not smaller than 10m and not larger than 50m. If set size is too small, the performance will be similar to value-value mapping method. If set size is too large, the result will possibly be the same as PRA.

After we have complete set division, we could use some specific models to assign a signal value for each node. To make all values assigned, we should first sort all the values that fall into current set. Signal power list after sorting can use as the input to the mapping model. Then we should divide the current set into several segments in equal size. Each segment maps to a distance value respectively. Distance value should be:

$$R_{\min} + i \cdot \Delta R (1 \le i \le s, \Delta R = \frac{R_{\max} - R_{\min}}{s}) \quad (2)$$

Then we could use similar way in PRA to map nodes in total S segments to different distance values respectively.

SPRA provides two different mapping models, including simple linear model and area-proportional model. These two, originating from PRA, are similar in mapping mechanism, but different in calculation method.

3.1. Simple Linear Model

Different from the model in PRA, this model in SPRA uses RSSI to determine the order of nodes. Nodes in *ith* segment (1<= i <= s) should be mapped to $R_{\min} + i \cdot \Delta R$. Here is example when number of node *n* equals to 8, the mapping result using simple linear model is given in Figure 2.

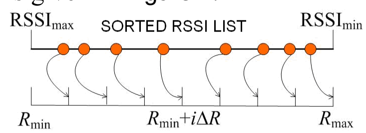

Figure 2 Mapping results using SLM

3.2. Area-proportional Model

This model divides a distance set into several rings with equal ratios.

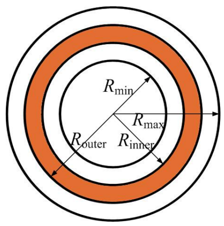

Figure 3 Area Proportional Model (APM)

As we can see from Figure 3, R_{min} and $R_{\max}$ are lower and upper bound of a distance value set. We divide the set into s parts, the *ith* part's inner and outer radius noted as R_{inner} and R_{outer}, this part's area can be calculated by Formula 3.

$$\begin{aligned} R_{inner} &= R_{\min} + (i-1)\Delta R \\ R_{outer} &= R_{\min} + i \cdot \Delta R \\ S_i &= \pi R_{outer}^2 - \pi R_{inner}^2 \\ &= \pi\Delta R\left[2R_{\min} + (2i-1)\Delta R\right] \end{aligned} \quad (3)$$

Note that $R_{\max}$ can be represented as $R_{\min}+s\,\Delta R$, area of the ring is given Formula 4

$$S = \pi R_{\max}^2 - \pi R_{\min}^2 = \pi\Delta R(2sR_{\min} + s^2\Delta R) \quad (4)$$

By now we can do subdivision according to Formula 5. After this work, the ith node should be mapped to a distance value of $R_{\min} + i \cdot \Delta R$.

$$\frac{2R_{\min} + \Delta R}{2sR_{\min} + s^2\Delta R} : \cdots : \frac{2R_{\min} + (2i-1)\Delta R}{2sR_{\min} + s^2\Delta R} : \cdots : \frac{2R_{\min} + (2s-1)\Delta R}{2sR_{\min} + s^2\Delta R} \quad (5)$$

Let $R_{\min}$ equal to 10 meters, and $R_{\max}$ equal to 20 meters, s equal to 2, which means we divide this area into two parts, n equal to 8. According to Formula 5, we can get that there are 3 and 5 nodes in each part. 3 nodes with higher RSSI are mapped to 15m, and rest of 5 nodes whose RSSI are relatively low are mapped to 20m. Figure 4 reveals the result.

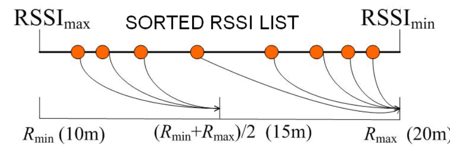

Figure 4 Mapping results using APM (s=2, n=8)

By now we do get results using our SPRA methods. Later in this paper, we will show that this method enhance the accuracy greatly while reducing the overhead comparing to PRA.

4. Ring Overlapping Localization algorithm

Ring Overlapping Localization Algorithm is another main component in our localization solution. It utilizes the mapping relationship from SPRA. When running ROL, we do not need to wait SPRA assign all node to correspond distance values. What we need from SPRA is only a set-to-set mapping relationship to determine which set a RSSI value belongs to.

4.1. Basic principle

There are typical two kinds of nodes in WMN networks. One kind is mesh routers, which distributed throughout the area and provide access service while working as routers at the same time. The other kind is mesh clients, including most of user equipments such as laptop, PDA, cell phone and etc. This kind of nodes is mainly focused in our ROL algorithm. In other word, we provide localization service mainly to mesh clients in WMN.

Existing methods in this field can be classified into two kinds. The first one is most common case, which requires equations of distances to different mesh routers and usually uses multilateration method to get results. Theoretically, we only need distance values towards no less than 3 mesh routes to get specific position in a same plane. As shown in Figure 5, if we use least-squares method or Kalman Filter method [15], we can get an even more precise result.

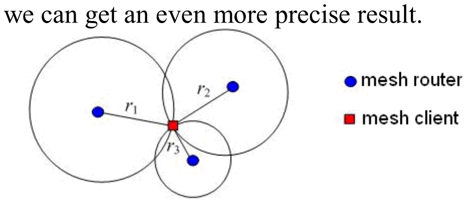

Figure 5 Route distance dependent algorithm

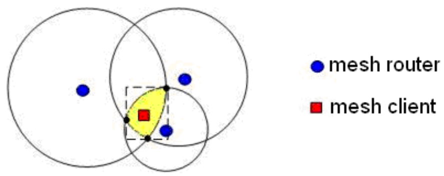

Figure 6 Coverage area based algorithm

However, there are always errors in measurement. So, when carried into practical use, these methods often get no less than a single result value, thus where coverage dependent algorithm thrived, as shown in Figure 6. This algorithm does not seek to get a single value of location, but utilize what we got to determine a possible area in which target node is. Centroid of such area is often used as the result.

As we discussed above, it is difficult to give a precise value of distance between mesh router and mesh client. However, algorithms above are all base on this point, which makes them unreliable.

In ROL, we use ring overlapping instead of circle overlapping to determine a target area. Since it is no need for us to get specific value of distance from a definite RSSI, we just need a series of upper and lower bounder which is provided by SPRA in advance.

ROL based on the premise that mesh clients can only get an upper and lower bounder of distance between it and a mesh router. We also use centroid of the intersect area as the result.

4.2. Algorithm design

In this section we primarily discuss some details of ROL algorithm. There are mainly two stages in this algorithm.

In the first stage, we should determine the ring overlapping area. This stage is assisted by SPRA. According to SPRA discussed above, we first choose a suitable signal transmission model or we carry out experiments to get mapping relations between RSSI and distance. Then we divide this kind of mapping relations into set-set mappings and build a table of it. When running ROL, a mesh client may receive signals from multiple mesh routers. For each signal, the mesh router gets its RSSI and lookup into the table to find what RSSI set it belong to. After it determined RSSI set, it can determine the distance set from which the upper bound and lower bound are got. Finally, according to the two values get from the table, the mesh route can draw a ring. When there are more than 3 rings overlapping on a same mesh client, we will get target area we want.

It is no use that we only get an overlapping area. Then in the second stage we provide a set of calculation methods to get a specific result from the area we got.

A quick start is to scan every possible point which is within every single ring. We can get points in the intersect area of the rings by this way. The arithmetic mean of location of these points is the centroid of the area. However, when the area of intersection is large or there are a great many of rings to judge, it is not an efficient way to do like this.

The Solution we use in ROL is to determine the bound of a possible intersection area, as is shown in Figure 7. The bounder is classified in to 4 values x_{left}, x_{right}, y_{top} and y_{bottom}. These values are determined by circle intersection points or circle bounder it self. It is obviously that we do not only get 4 values of this kind. Each time we calculate the intersection of two rings, we got 4 values like this. The rest work left is only to refresh these 4 values when calculating other ring intersections, as shown in Figure 8.

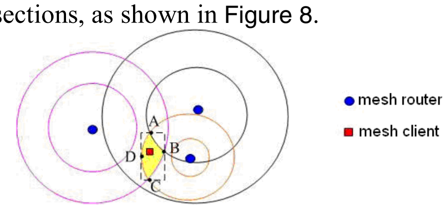

Figure 7 Ring Overlapping based localization algorithm

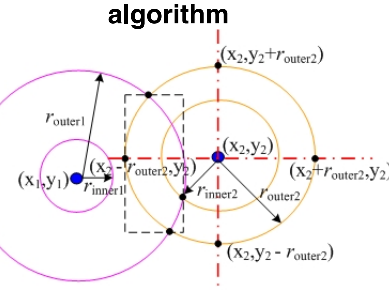

Figure 8 Determining bounders in ROL

The main idea of this part is to firstly get points' coordination which could possibly influence the size of question domain. Through continues comparing and updating these values, we finally get the maximum possible question area. Comparing to simple scanning method, this algorithm avoids most of the irrelevant points to be taken into account, and thus greatly reduced the works of calculation.

In ROL, a single mesh client can receive signals from multiple mesh routers. For each of two rings, we get bounders of result area. Then we can determine a rectangle after comparing different group of bounders. For each point in the rectangle, scan method is used to verify if current point is in the intersection area. In some cases, there may not be any point which belongs to all the rings. If so, we should choose areas whose points are mostly overlapped as the result. If a mesh client receives from N mesh routers, algorithm should

Table 1 (a) Set division results

Model	RSSI SET (dBW)	DIST SET (m)
FreeSpace (R= 50m)	-46 and above	1 ~ 3
	-46 ~ -52	3 ~ 6
	-52 ~ -57	6 ~ 10
	-57 ~ -60	10 ~15
	-60 ~ -65	15 ~ 25
	-65 ~ -70	25 ~ 44
	-70 ~-75	44 ~ 78
	-75 ~ -79	78 ~ 124
	-79 ~ -83	124 ~ 196
	-83 ~ -85	196 ~ 247
	-85 ~ -87	247 ~ 311
	-87 ~ -89	311 ~ 391
	-89 ~ -91	391 ~ 492
	-91 ~ -93	492 ~ 620
	-93 and below	620 ~ 750
Indoor Shadowing (R= 35m)	-66 and above	1 ~ 4
	-66 ~ -75	4 ~ 8
	-75 ~ -81	8 ~ 12
	-81 ~ -85	12 ~ 17
	-85 ~ -90	17 ~ 24
	-90 and below	24 ~ 35

be run for $\binom{N}{2}$ times. After chosen overlapping area, we should also determine point scale according to accuracy we want. Let Algorithm 1 and proceedings that computing how many rings a point is overlapped be the atom operations, time complexity of ROL can be represented as Formula 6

$$\binom{N}{2} + \left\lfloor \frac{x_{right} - x_{left}}{\text{point\_scale}} \right\rfloor \times \left\lfloor \frac{y_{top} - y_{bottom}}{\text{point\_scale}} \right\rfloor \quad (6)$$

Judging from Formula 5, the complexity of ROL should be $O(N^2)$. However, the latter component of this formula is not a constant. When the coverage is large and point scale is small, the cost of scanning is far more than the cost of determining the bounders. Besides, overlapping area may include a series of scattered and disconnected parts, as shown in Figure 9. In such situation, the target rectangle is filled with irrelevant points, which would result much unnecessary calculation. This is what ROL should solve in the future.

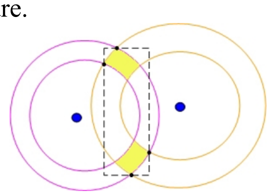

Figure 9 Disconnected overlapping areas

Table 1 (b) Set division results

Model	RSSI SET (dBW)	DIST SET (m)
Two-ray Ground (R =250m)	-51 and above	1 ~ 5
	-51 ~ -60	5 ~ 14
	-60 ~ -65	14 ~ 27
	-65 ~ -70	27 ~ 44
	-70 ~ -75	44 ~ 78
	-75 ~ -80	78 ~ 110
	-80 ~ -85	110 ~ 146
	-85 ~ -87	146 ~ 167
	-87 ~ -90	167 ~ 195
	-90 ~ -92	195 ~ 220
	-92 and below	220 ~ 250
Outdoor Shadowing (R =112m)	-58 and above	1 ~ 4
	-58 ~ -65	4 ~ 7
	-65 ~ -70	7 ~ 12
	-70 ~ -75	12 ~ 19
	-75 ~ -80	19 ~30
	-80 ~ -85	30 ~ 45
	-85 ~ -90	45 ~ 71
	-90 and below	71 ~ 112

5. Experiments and performance evaluation

5.1. SPRA (Subtle Partial Range Aware Algorithm)

In this section, we carry out some simulation experiments through NS-2 [16] in order to evaluate performance of SPRA. We generated two groups of scenarios, the first group of scenario contains 50 nodes and second group contains 100 nodes. In each group, we have 10 different scenarios. For each scenario, we calculate the distance of neighboring nodes with PRA and SPRA respectively. The calculation result will be compared to truth value to settle measurement error rates. Finally, we compare the measurement error rate between PRA and SPRA, and draw our conclusion from this comparison at last.

Because distance measurement is highly relative to wireless transmission models, so in this experiment, we choose all four different transmission models to eliminate this potential influence. They are FreeSpace, TwoRayGround and Shadowing Model, which are all supported by NS-2. We separate shadowing model into indoor-shadowing model and outdoor shadowing model by manipulate the value of route loss rate n and route loss variance σ. We set n = 2.5, $\sigma = 4$ for indoor shadowing model and $n = 3$, $\sigma = 7$ for outdoor shadowing model.

For each transmission model, we utilize a threshold tool provided by NS-2 in the first place to get the mapping list between RSSI and distance. Our calculation uses some of NS-2's default configuration. The transmission power of a wireless node is -5.5dBW. Signal frequency is 9.14×10^8Hz. The gain of both sending and receiving antenna is 1. Height of antenna is 1.5m. System loss is 1.

Mapping list varies greatly when utilizing different transmission model. Figure 10 reveals this phenomenon. Not only mapping rules, but also transmission radius, changing trends of functions, are various. Therefore, the principle of set division in SPRA can not be uniformly decided. It must be based on current environment's transmission model. For FreeSpace, which has a large transmission range and a stable trend in function image, set size should be relatively large. And when it comes to shadowing model, whose transmission range is small and changing rate is high, set size should be smaller than other models.

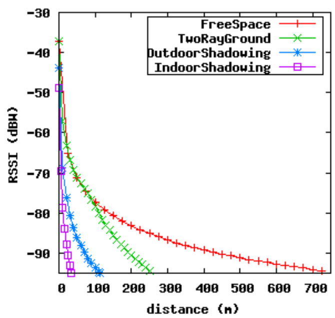

Figure 10 Mapping functions of different transmission models

After analysis these mapping relations, we do our division as shown in Table 1.We uses error rate as criteria of algorithm performance. Assume distance of two nodes is *d*, calculation result is *d'*, error rate of measurement is δ, there are *n* times of measurement in one scenario, total error rate of measurement of the scenario is Δ. We have the formula below.

$$\delta = \frac{|d' - d|}{d} \times 100\% \qquad \Delta = \frac{\sum_{i=1}^{n} \delta_i}{n} \tag{6}$$

In order to reduce the influence of some special case, we randomly generated 10 scenarios. The finally error rate will be the arithmetic mean of the 10 results.

For each transmission model, we carry out four groups of experiments, whose n = 50 and s = 5, n = 100 and s = 5, n = 50 and s = 10, n = 100 and s = 10 respectively. Note that n is number of nodes and s is the number of segments to map. For PRA and SPRA, we both use Simple Linear Model (SLM) and Area Proportional Model (APM) to run mapping procedure. The error rate of each case is shown in Table 2.

It is obviously that SPRA is more accurate than PRA. Judging from the whole, PRA's average error rate is 66.3%, while average error rate of SPRA on SLM is only 13.8%.

In scenarios where nodes are uniformly distributed, theoretically analysis results show that it is always lower error rate using APM than SLM. However, this does not supported by our experiments. This may be caused by two reasons. Firstly, experiments is two small for some of the transmission model such as TwoRayGround. Most nodes are distributed in a lower range of transmission. However in the APM, some of the nodes are mapped to a distance of transmission radius, which influence the measurement error rate of PRA using APM directly. On the other hand, in SPRA, the shadowing models have small transmission range. The possibility that nodes fall in each segment is even smaller. According to Formula 5, APM model will map most nodes to a larger distance. Because of low ratios, there may be not any nodes mapped to a smaller distance. This trend is more obvious when segment number *s* become larger. So, in shadowing model using SPRA, APM has a larger error rate than SLM.

To SLM, when node density increases, it tends to get a smaller error rate. This is because there are more neighbors when node density is larger. The possibility of nodes falling into each segment is also increased, which makes mapping more accurate.

In all, our experiment shows that SPRA is generally better than PRA. Besides, SPRA do not require much calculation, which makes it suitable for practical use.

5.2. ROL (Ring Overlapping based Localization algorithm)

We carry out experiments and evaluate performance of ROL in this section.

We design our experiments as follow. As for test environment, we set three nodes that do not move as mesh routers. We use laptops as mesh clients. In our experiment scenario, we randomly choose a set of points in nearby places. At same time we run our ROL algorithm on the client laptop while running the ROL, the client can get distance information between a mesh router and itself. Routers only need to broadcast their own location in a constant interval time so as to help client to localize itself. By comparing the calculation position and the ground truth, we can get error rate of ROL. The topology of our scenario is shown in Figure 11. We choose EDIMAX's EW-7206Apg as our AP [17]. Its standard transmission power is 15dBm, and it support 802.11a/b/g protocol. Our mesh client is an

Table 2 Error rate in distance measurements

	variables	PRA SLM	PRA APM	SPRA SLM	SPRA APM
FreeSpace	n=50, s=5	91.9%	158.0%	18.4%	9.4%
	n=50, s=10	81.7%	46.7%		17.0%
	n=100, s=5	48.0%	157.5%	10.4%	4.2%
	n=100, s=10	44.5%	95.2%		7.5%
TwoRay-Ground	n=50, s=5	25.2%	29.5%	15.6%	17.8%
	n=50, s=10	28.8%	43.9%		32.6%
	n=100, s=5	33.1%	74.7%	9.2%	9.5%
	n=100, s=10	27.2%	70.5%		17.8%
Outdoor Shadowing	n=50, s=5	86.6%	43.1%	23.6%	45.7%
	n=50, s=10	132.4%	66.5%		81.8%
	n=100, s=5	56.7%	74.6%	12.1%	23.1%
	n=100, s=10	74.7%	83.3%		41.6%
Indoor Shadowing	n=50, s=5	75.7%	33.5%	13.9%	34.6%
	n=50, s=10	65.2%	40.1%		80.2%
	n=100, s=5	50.6%	67.2%	7.1%	17.5%
	n=100, s=10	43.8%	70.0%		40.5%

Table 3 Mapping sets in our scenario

RSSI (dBm)	DISTANCE (m)
-18 and above	0 ~ 0.4
-32 ~ -18	0.4 ~ 1.2
-48 ~ -32	1.2 ~ 4.0
-56 ~ -48	4.0 ~ 9.0
-64 ~ -56	9.0 ~ 15.0
-80 ~ -64	15.0 ~ 20.0
-80 and below	20.0 ~ 40.0

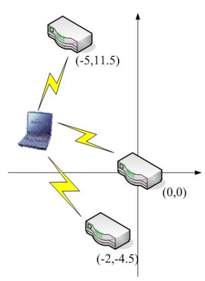

Figure 11 Topology of our scenario

IBM T23 laptop with a 1.1GHz CPU, 512Mb memory, and Windows XP on it. The wireless card on the mesh client is Lucent's Orinoco Silver wireless card, which supports 802.11b protocol.

ROL needs offline measurement in advance, if we can not decide what transmission model to choose. Windows Network Driver Interface Specification (NDIS) [18] provide an interface for retrieve signal power strength as RSSI.

In our experiment, we should filter APs' MAC addresses that are not within the router list in the first place. Wireless signal always fluctuates, and in order to eliminate the error incurred by this fluctuation, we use values of arithmetic mean of multiple results in continues period of time.

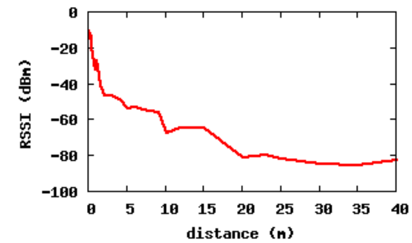

Figure 12 Mapping RSSI and distance

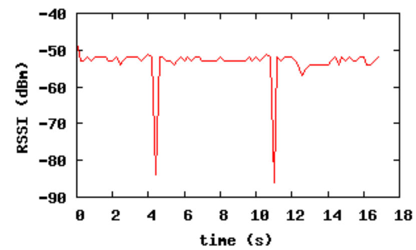

Figure 13 Fluctuation of signal

After carefully measurements, we get the mapping rules for our experiment scenario, which is shown in Figure 12. According to that mapping relation, we divide RSSI and distance into correspondent sets, as shown in Table 3. The result of running ROL at a certain point can be seen in Figure 13. However, when overlapping area scatters and disconnected, accuracy of ROL degrades, which is shown in Figure 14.

We eventually measured a series of places and compared calculated value and ground truth. Result is given in Figure 15. Because of the fluctuation of signal power, it is common that we do not get a single result even the node is not moving. We choose arithmetic mean of these results as estimation value of ground truth. According to the data revealed in Figure 15, the RMSE of ROL is 3.11 meters, which is better than RADAR method. Figure 15 and Figure 16 are the snap shots of our localization application which is developed on windows platform. The scattering overlapping area problem is shown in Figure 16.

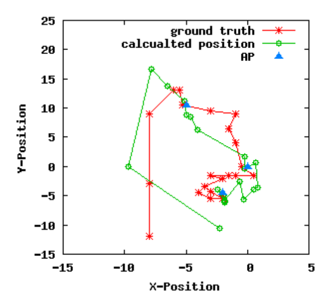

Figure 14 ROL performance

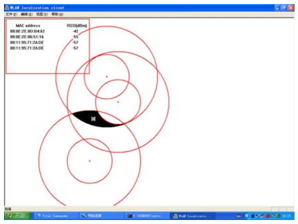

Figure 15 Running ROL

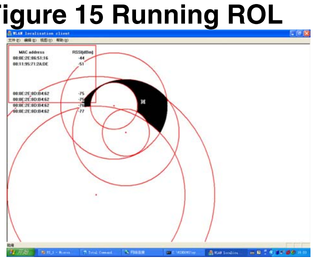

Figure 16 Overlapping area scatters

6. Conclusion and future work

In this paper, we have proposed a localization solution for Wireless Mesh Networks (WMN); consisting of Subtle Partial Range Aware (SPRA) algorithm, and Ring Overlapping based Localization algorithm (ROL). Both of which, according to our evaluation, have a better performance than existing methods. Experiments also show that our algorithm is cost-effectiveness and consumes little system resources, since the only thing to do of ROL is to receive signal and refresh the location. Therefore, it wouldn't be a problem for our approach to scale.

However, there still exist a number of unsolved problems: how to handle the scattering overlapping area in ROL, how to better eliminate signal fluctuation, etc. We also plan to implement our approach in campus of Peking University. It is believed that the feedback from this project will surely help us to improve our algorithm.

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