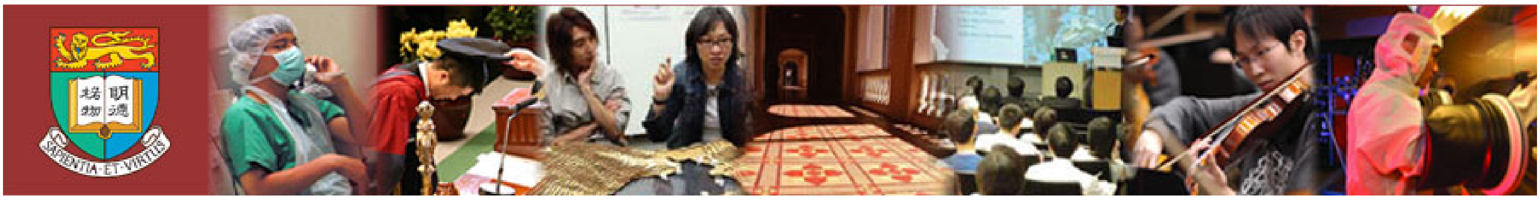

Title	An iteratively Reweighted Least Square algorithm for RSS-based sensor network localization
Author(s)	Qiao, D; Pang, GKH
Citation	The 2011 IEEE International Conference on Mechatronics and Automation (ICMA 2011), Beijing, China, 7-10 August 2011. In Proceedings of ICMA, 2011, p. 1085-1092
Issued Date	2011
URL	http://hdl.handle.net/10722/135859
Rights	Creative Commons: Attribution 3.0 Hong Kong License

Proceedings of the 2011 IEEE
International Conference on Mechatronics and Automation
August 7 - 10, Beijing, China

An Iteratively Reweighted Least Square Algorithm for RSS-based Sensor Network Localization

Dapeng Qiao, Grantham K.H. Pang
Department of Electrical and Electronic Engineering
The University of Hong Kong
Pokfulam Road, Hong Kong
{dpqiao, gpang}@eee.hku.hk

***Abstract*— In this article, we give a new algorithm for localization based on RSS measurement. There are many measurement methods for localizing the unknown nodes in a sensor network. RSS is the most popular one due to its simple and cheap hardware requirement. However, accurate algorithm based on RSS is needed to obtain the positions of unknown nodes. Recent algorithms such as MDS(Multi-Dimensional Scaling)-MAP, PDM (Proximity Distance Matrix) cannot give accurate results based on RSS as the RSS signals always have large variations. Besides, recent algorithms on sensor network localization ignore the received signal strength (RSS) and thus get a disappointing accuracy. This is because they are mostly focused on the difference between the estimated distance and the real distance. This paper introduces a target function - signal-based maximum likelihood (SML), which uses the maximum likelihood based on the directly measured RSS signal. Inspired by the SMACOF (Scaling by Majorizing A COmplicated Function) algorithm, an iteration surrogate algorithm named IRLS (Iteratively Reweighted Least Square) is introduced to solve the SML. From the simulation results, the IRLS algorithm can give accurate results for RSS positioning. When compared with other popular algorithms such as MDS-MAP, PDM, and SMACOF, the error (distance between the estimated position and the actual position) calculated by IRLS is less than all the other algorithms. In anisotropic network, IRLS also has good performance.**

Keywords- sensor network, localization, RSS, signal-based maximum likelihood, SML, SMACOF, IRLS.

I. INTRODUCTION

Location estimation is needed in many applications such as remote patient monitoring, package and personnel tracking, location-based messaging, environment monitoring, and wildlife habitat monitoring. In these systems, there are usually hundreds of or even thousands of low-cost sensor nodes. In addition, based on the signals received from other nodes, it would know its distance from these nodes. Estimation on the location of these nodes is an important issue for any sensor network. It is necessary to accurately localize the sensors in order to measure data which is geographically meaningful. This localization issue has been studied by many researchers and there are many different methods and algorithms [1-5] dealing with this situation.

For applications like automatic guidance and wildlife habitat tracking, GPS-like devices are widely used. However, GPS devices are expensive and inefficient on power consumption [1]. Moreover, the signal of GPS requires line-of-sight between the receiver and satellites and cannot go through the walls of buildings. Thus, in sensor networks with a large number of sensor nodes, attaching a GPS device to each node is not practical. In most cases, there are only a few nodes with known positions in the whole sensor network, while others are unknown. The only information between the known nodes and the unknown nodes is the communication among them, which can imply the distance or angle between the nodes. Localization in a sensor network is to utilize any useful information for position estimation of the unknown nodes.

The problem considered in this paper is as follows. A sensor network is assumed to have hundreds or thousands of nodes in a region, and the nodes can communicate with each other. Some of the nodes have pre-known positions, but most of them are with unknown positions. The localization of the nodes depends not only on the location of the pre-known nodes (anchors), but also on the type of measured information among the nearby nodes, which leads to localization methods such as TOA (time-of-arrival), AOA (angle-of-arrival), and RSS (received signal strength).

To improve the accuracy of localization, the measurement between the nodes is the most important factor, which is dependant on the hardware. With the given hardware of the sensors and the locations of the anchors, the algorithm used for localization is vital to the position accuracy. Besides the accuracy, the algorithms should also take the computation complex into consideration which is restricted by the hardware configuration (mainly the computation capability) of the network. Thus, the kind of algorithms with high accuracy and less computation cost is desirable. However, every localization algorithm should be based on a certain localization method, or the combination of several localization methods.

A. *Received signal strength (RSS)*

The distance between two nodes can be estimated by the signal strength (RSS). The transmitted signal can be RF (radio frequency), acoustic or other signals. RSS is always thought to be a coarse method because the RSS signal is not as stable as TOA. However, this method is simple in the configuration of the nodes and low-cost. Furthermore, RSS does not need additional elements or energy requirement while wireless nodes in sensor network use RF signal to communicate with each other. For sensor network with low-cost nodes, RSS-based distance measurements are preferred.

Radio frequency signals mainly suffer from multipath and shadowing, which cause variations in RSS measurement. When the transmitter and the receiver are in contact, RSS in the receiver's side is not a constant, but varies due to shadowing and multipath. Moreover, in a 2D sensor network, one node may contact with other nodes in different directions. In order to have equal connection ranges in all directions, the nodes' antenna is always omni-directional. However, even the omni-directional antenna does not perform perfectly uniformly in all directions. The variations due to shadowing, multipath, and different directions can be expressed together as the standard deviation in the log-normal distribution model.

B. Related work

Doherty et al [2] model range and angular constraints in sensor network localization as convex constraints. The resulting minimization problem can be solved efficiently using semi-definite program (SDP). SDP in some particular conditions can become linear programming (LP) to be solved more efficiently. Hence, the problem becomes an issue on minimizing a linear function over a polyhedron.

Triangulation and multi-lateration greatly depends on the density of the anchors. If there are not enough anchors, the error of the estimation of unknown nodes will be accumulated and become very inaccurate. Proximity distance matrix (PDM) first appears in [3], which aims to build a transformation between the proximity and the distance. It is used to estimate the distance to at least three anchors of every unknown node. Then multi-lateration or triangulation can be used to obtain the positions of unknown nodes.

Nonlinear dimensionality reduction is also used in sensor network localization. Chengqun et al. [4] employ the geodesic distances to measure the dissimilarity between sensors, and propose a centralized algorithm based on isomap technique [7]. In specific, they first build the neighborhood graph based on the sensors and their pair-wise distance, and then compute the geodesic distance of each pair of sensors. Finally, they construct the 2D embedding and obtain the relative coordinate using MDS. Since the performance of isomap is sensitive to the parameter, in order to alleviate the influence of the parameter, they also propose an adaptive parameter selection procedure based on the true locations of the anchors and their transformed locations.

Patwari et al [5] briefly mentioned that the manifold learning techniques (including isomap) can be used for localization problem under the spatially correlated sensor model. Generally, this algorithm is similar to the classic algorithm MDS-MAP [6], because isomap can be considered as a geodesic distance version of the MDS. Instead of using the Euclidean distance for embedding, isomap considers the geodesic distance on a weighted neighbouring graph.

Multidimensional scaling (MDS) is first used as a statistical technique in information visualization for exploring similarities or dissimilarities in data [6, 7]. It also has the ability to calculate the positions of the unknown nodes based on the distance between them. However, MDS obtains result only when distances between any two nodes are known previously. Some researchers employ MDS as the core step in their algorithms. MDS-MAP [6] utilizes MDS and obtains a success on positioning with a small variation of distance measurement. First, based on the connectivity and distance information between nodes, a rough estimate of relative node distance is made. Then relative positions are obtained by Singular Value Decomposition on the estimated distance information matrix. Finally absolute positions of the unknown nodes are estimated. The computation complexity of this method is about $O(n^3)$ time for a sensor network of n nodes. Another efficient algorithm, SMACOF (Scaling by Majorizing A COmplicated Function), [8] uses an iterative method on the issue of sensor network positioning. However, the convergence of this method cannot be guaranteed.

II. PROBLEM STATEMENT

A. RSS propagation

Due to the simple and cheap hardware requirement, RSS is the most popular measurement nowadays. The accuracy of positioning based on RSS depends on the model of RSS propagation and the algorithm used for estimating the positions. On the model of RSS, the relationship between the RSS value and the 1D distance can be estimated. However, in reality, the sensor networks are always in 2D or 3D, which means the nodes in a sensor network may have different models in different directions. Therefore, the antenna of each sensor should be omni-directional. For an omni-directional antenna, the relationship between RSS value and the distance in every direction should be similar. One example is from [9]. No matter what the pattern is in vertical, the horizontal pattern is circular as shown in Fig. 1

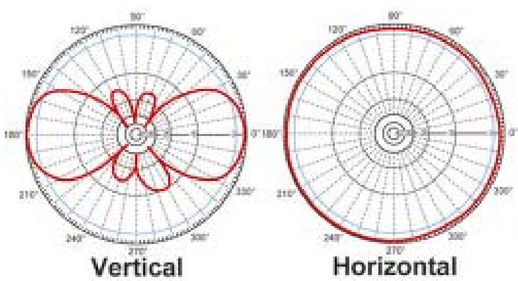

Fig. 1 One example of the antenna pattern, which is omni-directional in the horizontal plane [9]

Wireless signal power decays proportional to $d^{-\alpha}$, where d is the distance between the transmitter and the receiver; α is the 'path-loss exponent', typically a value between 2 and 4 [10]. The signal strength model is as follows:

$$rss = rss^{d_0} - 10\eta \log_{10}(\frac{d}{d_0}) + N_{\sigma_N} \quad (1)$$

where d is the actual distance to the measured point, rss^{d_0} is the received signal strength at reference distance d_0, η is the path-loss exponent. N_{σ_N} is a zero-mean noise which is a normally distributed random variable with variance σ_N corresponding to the fading. Both η and σ_N are calibrated from the environment. The higher the value of η is, the more the signal strength is attenuated, rendering a shorter average transmission range for each node. Random variable N_{σ_N} corresponds to the amount of environmental noise, which affects the accuracy of the measured distance [11].

To simplify equation (1), let $d_0=1$, the model becomes:

$$rss_{i,j} = rss_i^1 - 10\eta \log_{10} d_{i,j} + N_{\sigma_N} \tag{2}$$

where $d_{i,j}$ is the distance between node i and j. Here we assume that node i is the transmitter and node j is the receiver. rss_i^1 is a constant, which is inherent of node i. If there is a receiver one meter away from the transmitter node i, the received signal strength obtained by this receiver is rss_i^1. This can be expressed by $rss_i^1 = rss_i^{d_0=1}$. $rss_{i,j}$ means the strength of the signal which is transmitted from i and received by j.

Different transmitters may have different value of rss_i^1 due to different transmission power or other hardware characteristics. Even in a typical ad hoc network with all the sensors designed to have the same function, the transmission power of all the sensors cannot be assumed to be identical. Therefore, in a sensor network with n nodes, rss_i^1 i=1,2,3,…,n should be calibrated in advance. It is then assumed that these values remain unchanged with proper design of the transmitter circuitry. Further discussions on RSS measurement algorithms are all based on the above model with equation (2).

B. *Pre-known Information*

There are n nodes in the sensor network, in which the first m nodes' positions are unknown. Therefore, the unknown parameters are $\{\mathbf{z}_1, \mathbf{z}_2, ..., \mathbf{z}_m\} = \{x_1, y_1, ..., x_m, y_m\}$, which are the coordinates of the unknown nodes. The variable received signal strength $rss_{i,j}$ is measured and recorded as $\widetilde{rss}_{i,j}$. Suppose an unknown node i can hear l nodes, which include the node j. The set H is the set of all the pairs in which the two nodes can receive signal from each other. Obviously, the pair of the nodes i, j, recorded as (i, j), belongs to H. The meaning of the symbols used is given below:

TABLE I. SYMBOLS IN THIS ARTICLE

Notation	Description
D	Dimensions of coordinate in the sensor network (D=2 in this paper)
n	Number of total sensors
m	Number of unknown sensors
$\mathbf{z}_i = [x_i, y_i]^T$	Actual coordinate of node i, (i =*1,2,…,n*)
$\hat{\mathbf{z}}_i = [\hat{x}_i, \hat{y}_i]^T$	Estimated coordinate of node i, (i =*1,2,…,n*)
$Z = [\mathbf{z}_1{}'; \mathbf{z}_2{}'; ...; \mathbf{z}_n{}']$	The matrix containing all $\mathbf{z}_i$
$d_{i,j}$	Actual distance between node i and j, (*i,j=1,2,…,n*)
$rss_{i,j}$	Actual strength (dB) of the signal transmitted from node i and received by node j (*i,j=1,2,…,n*)
$\widetilde{rss}_{i,j}$	Measured strength (dB) of the signal transmitted from node i and received by node j, (*i,j=1,2,…,n*). It does not equal to $rss_{i,j}$ due to noise in measurement.
rss_i^1	$rss_i^1 = rss_i^{d_0=1}$, strength (dB) of the signal transmitted from node i and received by a receiver, if this receiver is one meter away from node i. (i =*1,2,…,n*)
η	Path-loss exponent
N_{σ_N}	White noise of the RSS signal, which is a zero-mean normally distributed random variable with variance σ_N
σ_N	Variance of N_{σ_N}
H	If a pair of nodes can communicate with each other, this pair of nodes belongs to H. H is a set consisting of all pairs with this property.

III. THE ALGORITHM: SML & IRLS

To employ RSS value directly, a target function using signal-based maximum likelihood (SML) is developed, which is anticipated to be more accurate than others which are based on the distances values. IRLS (Iteratively Reweighted Least Square) will be introduced, which is an iterative method to solve the new target.

A. *Signal-based Maximum Likelihood (SML): New Target*

This section applies the maximum likelihood on the received signal strength to give the target function. Assume

- the probability density function of $rss_{i,j}$, $(i, j) \in H$ is $P[rss_{i,j}; (x_1, y_1, ..., x_m, y_m)]$, $x_1, y_1, ..., x_m, y_m$ are unknown,
- $\widetilde{rss}_{i,j}$, $(i, j) \in H$ is one measurement

Due to maximum likelihood, the optimal estimated value of $\{x_1, y_1, ..., x_m, y_m\}$ would make the product of the probability density functions of $\widetilde{rss}_{i,j}$ (for all pairs $(i, j) \in H$) maximum.

$$\begin{cases} \{\hat{x}_1, \hat{y}_1, ..., \hat{x}_m, \hat{y}_m\} = \underset{x_1, y_1, ..., x_m, y_m}{\arg\min} \,(-L) \\ L = \prod_{(i,j)\in H} P[\widetilde{rss}_{i,j}; (x_1, y_1, ..., x_m, y_m)] \end{cases} \tag{3}$$

where $\{\hat{x}_1, \hat{y}_1, ..., \hat{x}_m, \hat{y}_m\}$ is the estimation of $\{x_1, y_1, ..., x_m, y_m\}$.

From (2), the variable $rss_{i,j}$ varies according to the Gaussian distribution, i.e.

$$P[rss_{i,j}; (x_1, y_1, ..., x_m, y_m)] = \frac{1}{\sqrt{2\pi}\sigma_N} \exp\left[-\frac{\left(rss_{i,j} - rss_i^1 + 10\eta \log_{10} d_{i,j}\right)^2}{2\sigma_N{}^2} \right] \tag{4}$$

where $d_{i,j} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}$.

Take the logarithm of L and find the minimum, the unknown coordinates $\{\hat{x}_1, \hat{y}_1, ..., \hat{x}_m, \hat{y}_m\}$ can be obtained by

$$\begin{cases} \{\hat{x}_1, \hat{y}_1, ..., \hat{x}_m, \hat{y}_m\} = \underset{x_1, y_1, ..., x_m, y_m}{\arg\min} \ (L_{SML}) \\ L_{SML} = \sum_{(i,j)\in H} \left(\widetilde{rss}_{i,j} - rss_i^1 + 10\eta \log_{10} d_{i,j}\right)^2 \end{cases} \tag{5}$$

Function (5) is the target function based on the maximum likelihood with known RSS measurement. This is based on the RSS, thus called signal-based maximum likelihood (SML). The following section gives the solution of the above target function.

B. *IRLS: A Solution for SML*

Inspired by the SMACOF algorithm, one solution of SML can be reached using an iterative surrogate function. However, SMACOF is based on the TOA, which has the target different from that in RSS positioning. The focus will become: how to find an iterative surrogate function to solve SML? IRLS can solve SML using the iterative surrogate idea.

The algorithm steps of IRLS are:

1. Start with $Z^{(0)}$ and $w_{ij} = 1$; ($Z^{(0)}$ is random)
2. Find $Z^{(k+1)} = \arg\min \sum_{i>j} w_{ij} \left| d_{ij}(Z^{(k)}) - d_{ij}(\widetilde{rss}) \right|^2$ using SMACOF (shown in 2a, 2b, and 2c)
   2a. Start with $X^{(0)}$; ($X^{(0)} \leftarrow Z^{(k)}$)
   2b. Iterate
   $$X^{(k+1)} = V^{\dagger} \left(\sum_{i>j} \frac{d_{ij}(\widetilde{rss})}{d_{ij}(X^{(k)})} A_{ij}\right) X^{(k)} \tag{6}$$
   where A_{ij} is the matrix with below elements:
   $a_{ii} = a_{jj} = 1, a_{ij} = a_{ji} = -1$, other elements are 0;
   $V = \sum_{i>j} A_{ij}$;
   $V^{\dagger}$ is the pseudo inverse of V;
   $d_{ij}(X^{(k)})$ is $d_{i,j}$ derived from location matrix $X^{(k)}$;
   $d_{ij}(\widetilde{rss})$ is $d_{i,j}$ derived from measurement $\widetilde{rss}_{i,j}$;
   2c. Increment iteration time $k \leftarrow k+1$ go to 2b until the result converges (loop 1),
   2d. Give the final value of $X^{(k+1)}$ to $Z^{(k+1)}$.
3. Update weights
   $$w_{ij}^{(k+1)} = \frac{\log_{10} d_{ij}(Z^{(k+1)}) - \log_{10} d_{ij}(\widetilde{rss})}{2\ln[10(d_{ij}(Z^{(k+1)}) - d_{ij}(\widetilde{rss}))] \times d_{ij}(Z^{(k+1)})}$$
4. Increment iteration time $k \leftarrow k+1$, go to 2 until the result converges (loop 2).

C. *Change Relative Positions to Actual Positions*

Like the classical MDS, SML & IRLS give the relative positions, which should be changed/aligned into the actual positions using known nodes. As we know, three points will define a plane. Thus only 3 known nodes are needed for aligning. A formula to get actual positions using relative positions and 3 anchors can be found in [12].

IV. DETAILED ANALYSIS

This section simulates the IRLS, and chooses the suitable iteration time based on the simulation result. To the non-convergence situations, non-convergence treating is introduced. For improving the accuracy, a method is developed to choose three anchors for aligning the relative positions to the real positions.

A. *Parameters for simulation of IRLS*

We first describe the setting of parameters used for the simulation. From [3, 7], it is reasonable to set the parameters as in TABLE II. The parameters σ_N, and η have been introduced before. $rss_{\min}$ is the minimum signal strength that the nodes can receive.

TABLE II. SETTING OF THE PARAMETERS FOR SIMULATION

$rss_{\min}$	η	$\sqrt{\sigma_N}$
-120 dB	3.5	3

The situation is assumed as follows:

1. There are totally 100 nodes randomly located in a square of [0, 10] by [0, 10].
2. There are three nodes with known positions (anchors).
3. RSS between any pairs of nodes are measured as long as the RSS value is larger than $rss_{\min}$. The measurement $\widetilde{rss}_{i,j}$ is assumed to have a Gaussian distribution with the mean value of $rss_{i,j}$, and the standard deviation of $\sqrt{\sigma_N}$.

The mean value of the measurements $\widetilde{rss}_{i,j}$ is

$$mean(\widetilde{rss}_{i,j}) = rss_{i,j} = rss_i^1 - 10\eta \log_{10} d_{i,j} \tag{7}$$

where $d_{i,j} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}$, $(i, j) \in H$.

$\widetilde{rss}_{i,j}$ is generated by a Gaussian distribution generator in Matlab.

$$\widetilde{rss}_{i,j} = \text{normrnd}(\text{mean}(\widetilde{rss}_{i,j}), \sqrt{\sigma_N}) \tag{8}$$

Therefore, the known information includes $\mathbf{z}_i = [x_i, y_i]^T$ (*i,j=1,2,*3), $\widetilde{rss}_{i,j}$ (*i,j=1,2,…,n*), rss_i^1 (*i=1,2,…,n*), and η.

rss_i^1 for nodes *i=1,2,…,n* are all set be near to -55 dB. In the following simulations, the values should be in the range of -45dB to -65 dB.

Evaluation on the performance of the methods is based on the error between the actual position and the estimated position of the unknown nodes:

$$error\ per\ node = \frac{\sum_{i=1}^{m-n} \sqrt{(x_i - \hat{x}_i) + (y_i - \hat{y}_i)}}{m-n} \tag{9}$$

The result of IRLS is very accurate as shown in Fig. 2. Fig. 3 shows the *error per node* when the iteration time increases. The *x*-coordinate: iteration time indicates how many time does iteration equation (6) run. The steps of IRLS contain two loops: loop 2 is the update of the weight, which includes loop 1. Loop 2 is run 5 times totally, loop 1 is set 30 times for maximum. Therefore, iteration function (6) is run 5*30=150 times for maximum. But 150 is rarely reached because we break loop 2 when the changes compared with last iteration is too small. Fig. 4 shows the SMACOF, which also runs iteration function (6) for the same times as IRLS does. But the final error per node is 0.3906, much larger than 0.1659 of IRLS. Thus, from Fig. 3 and Fig. 4, IRLS is a more accurate algorithm when compared with SMACOF.

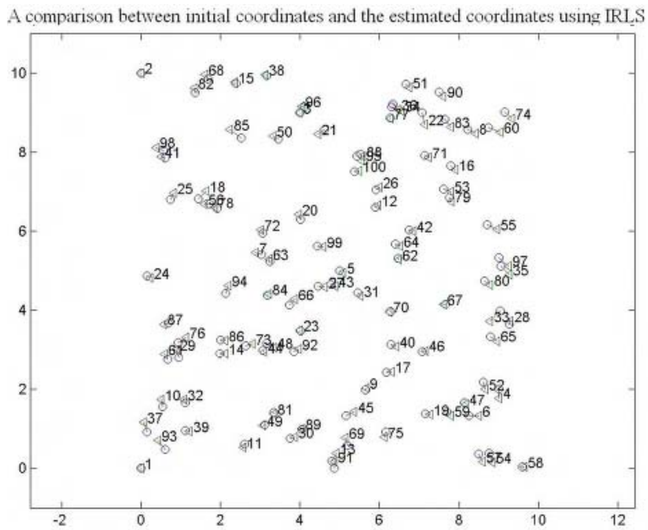

Fig. 2 The estimation result of IRLS in 100-node network (triangles are estimated positions; circles are actual positions)

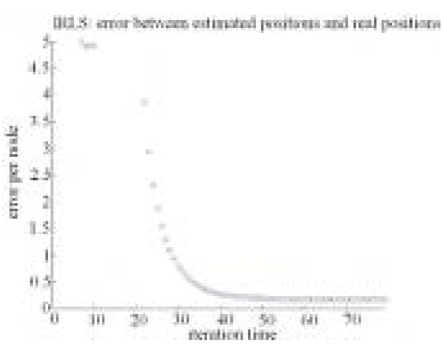

Fig. 3 Estimation in different iteration times of IRLS

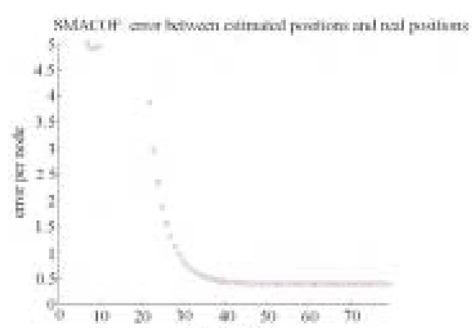

Fig. 4 Estimation in different iteration time of SMACOF

B. Choosing of Iteration Time

The iteration times of loop 1 and loop 2 can be changed. From Fig. 3, we find the iteration converges quickly. There should be great room to decrease iteration time to ease computation pressure.

If we decrease the iteration time of loop 1, the weight will be updated less frequently, which means the characteristic of IRLS will not be used. That will mean IRLS would get a very similar result like SMACOF. If the loop 1 is run 5 times, the weight update will be run 4 times (Initial weight does not count in). Take the iteration in Fig. 3 for example, the weight update is run 4 times in Fig. 5.

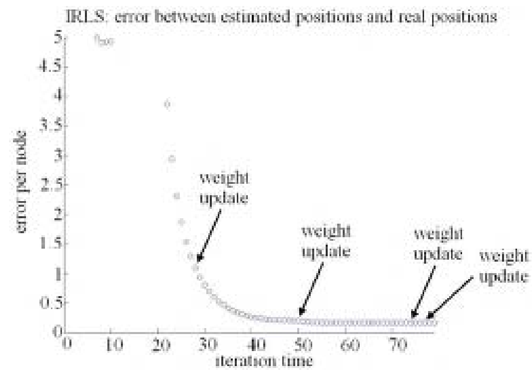

Fig. 5 Weight update of Loop 1

If we decrease the iteration time of loop 2, the convergence will not be easily reached. As shown in Fig. 6, convergence speed is decreased by a more frequent weight update. When the weight is updated in 10 iterations, the slope for convergence is not as big as that in Fig. 5. The optimum choice is: 5 times for loop 1, 25 times for loop 2 after many simulations of trying the values. 25 may not be reached because loop 2 breaks when the results are very close to the last iteration.

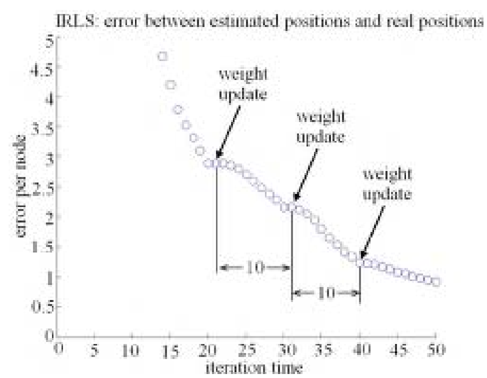

Fig. 6 Convergence speed is decreased when iteration time of loop 2 is too small, which is 10

C. Dealing with Convergence

There is no theoretical base to guarantee the iteration of IRLS to be always global convergent. The SMACOF algorithm, like our IRLS algorithm, does not guarantee on convergence. However, much better results can be obtained than the conventional algorithms. More experiments on convergencechecking are done with different number of nodes. The rate of convergence is evaluated as shown in Fig. 7. Besides, the experiments in centralized IRLS, which are conducted with 100 nodes, are all convergent. Therefore, generally speaking, the rate of be convergent is growing with the increase in the number of nodes. The non-convergence occurs randomly with no rules. Based on its random occurrence, we can repeat the algorithm for another time till no non-convergence occurs. Actually when the rate of convergence is nearly 0.9, very near to 100%, repeating the algorithm will not increase the computation complex greatly.

To avoid the non-convergence situations, we use the following methods.

1. When non-convergence occurs, we repeat the algorithm.
2. The scale of network can be adjusted to increase the probability of convergence. From Fig. 7, the best scale of sub-graphs should be more than 20.

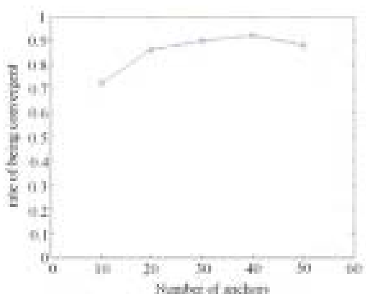

Fig. 7 Rate of being convergent

D. Choice of Anchors

As stated before, aligning the relative position only needs 3 anchors, while there are usually more known nodes in a network. The choice of three suitable anchors is an important step to make the algorithm accurate. The choice of the anchors will affect the accuracy of the algorithm. It is desirable that the three anchors are far apart enough, i.e. the area of the triangle with anchors at the corners should be larger than a certain value.

V. PERFORMANCE OF CENTRALIZED IRLS

For comparison with other popular algorithms whose input is the distance, not the RSS value, we first need to change the RSS value into distance. The known data for SML includes $\widetilde{rss}_{i,j}$, rss_i^1 , and η. However, for MDS-MAP, PDM, and SMACOF, the distance $\tilde{d}_{i,j}$, which is derived from $\widetilde{rss}_{i,j}$, is needed in their steps for calculation. Due to the relationship between the distance and RSS in (2), $\tilde{d}_{i,j}$ is obtained from the measured distance $\widetilde{rss}_{i,j}$ by the equation (10) and the logarithmic relationship between $\tilde{d}_{i,j}$ and $\widetilde{rss}_{i,j}$ is shown in Fig. 8,

$$\tilde{d}_{i,j} = 10^{-\frac{\widetilde{rss}_{i,j} - rss_i^1}{10\eta}} \tag{10}$$

With the above additional parameters, the estimated position for the unknown nodes can be estimated, from SML&IRLS and other algorithms, respectively.

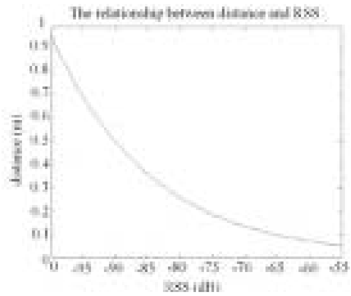

Fig. 8 The relationship between distance $\tilde{d}_{i,j}$ and RSS $\widetilde{rss}_{i,j}$

The parameters for simulation has been introduced in section IV. The evaluation on the performance of the algorithms is also based on the error per node in equation (9).

To decrease the effect of the sudden appearance of too big or too small number in the Gaussian distribution generator (8), the simulation including the procedure to generate Gaussian distribution $\widetilde{rss}_{i,j}$, is conducted for 20 times. The mean error for 20 times' simulation is recorded.

In current technology, omni-directional nodes' variance σ_N is: $\sqrt{\sigma_N}$ varis from 3 to 12. When σ_N is large, the estimation result will be very coarse. In this simulation, we get the performance of the four algorithms MDS-MAP, PDM, SMACOF, and IRLS under five values of standard deviation $\sqrt{\sigma_N}$: 0.5, 1, 3, 5, 7. The current hardware implementation can only realize standard deviation with values of 3, 5 and 7. With five different values of standard deviation, the mean error is shown in Fig.9. The result shows that MDS-MAP, PDM are disabled under RSS measurement with large standard deviations. IRLS can obtain acceptable accuracy when standard deviations are large. Besides, compared with the other three, IRLS greatly improved the estimation accuracy.

Fig. 10 shows the accuracy of the four algorithms while the sensor network has different number of nodes: 30, 50, 100, 200. In this case, the standard deviation of RSS signal is $\sqrt{\sigma_N}$ =3, which is common in RSS measurement. From the simulation, MDS-MAP and PDM obtain disappointed accuracy. SMACOF can give a better result, but the best one is IRLS. IRLS performs well in the large scale networks with the error at least 60% less than others. With the scale of the sensor network increasing, IRLS can give better accuracy. The accuracy of RSS-positioning estimation is also affected by the range of the nodes. Fig. 11 and Fig. 12 show the effect of the range in network with 100 nodes and 50 nodes, respectively. In such a large standard deviation ($\sqrt{\sigma_N}$ =3), no algorithm performs well under all the different ranges. However, when the range is larger (minimum RSS is smaller than -85dB), IRLS is accurate.

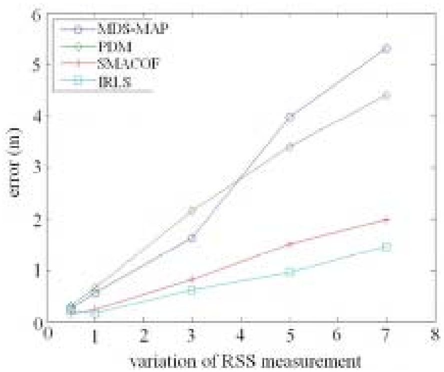

Fig. 9 Comparison on the accuracy in 50-node situation with different standard deviation

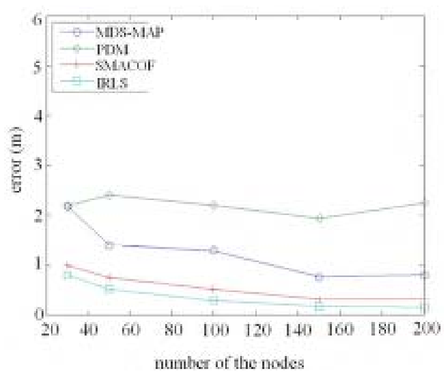

Fig. 10 Comparison on the accuracy with difference scale of the sensor network

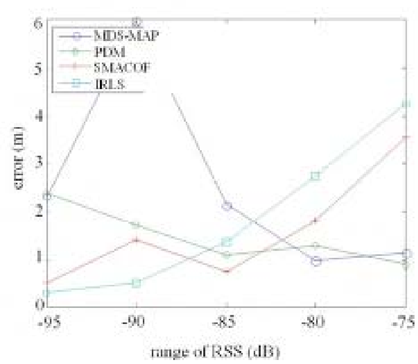

Fig. 11 The effect of range in a 100-node network

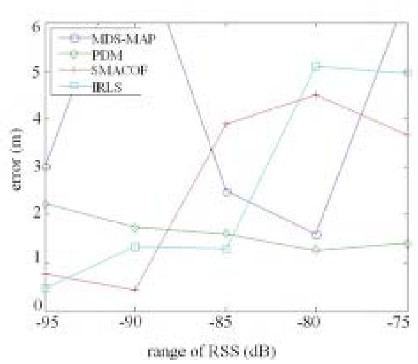

Fig. 12 The effect of range in a 50-node network

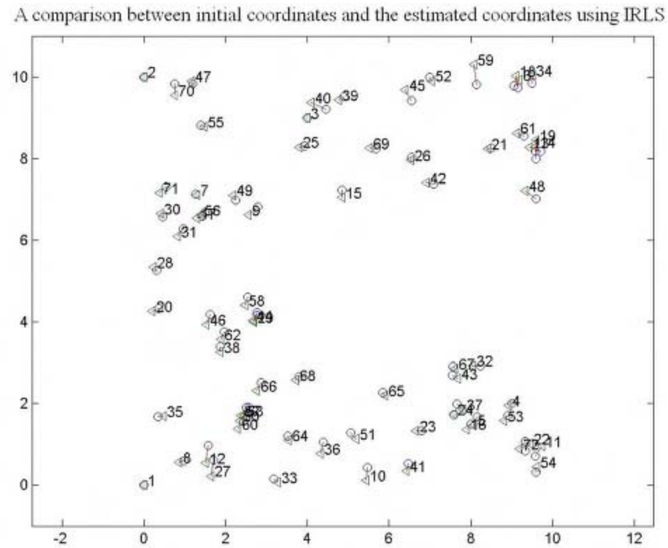

Fig. 13 IRLS performance in the C-shape network (triangles are estimated positions; circles are actual positions)

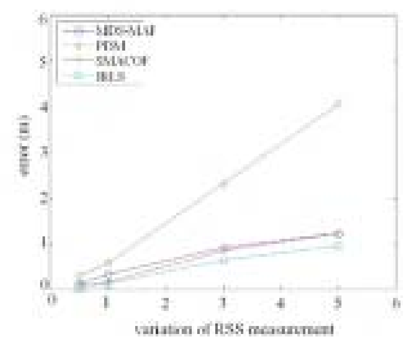

Fig. 14 Comparison on the accuracy of the four algorithms in c-shape network

The density of the nodes in a network is not always uniform. Current algorithms cannot perform well in anisotropic networks. Some researchers try to find suitable algorithm in anisotropic networks. IRLS obtains good result in an anisotropic network (C shape) as shown in Fig. 13. Not only in the large standard deviation situations, it is also better than other algorithms in small standard deviation, which is shown in Fig. 14.

From the above simulations, IRLS is shown to be accurate in both isotropic and anisotropic networks. The robustness of IRLS is also shown. IRLS is more robust to RSS variations than other algorithms (Fig. 9). MDS-MAP is sensitive to the signal variations due to the inherent emphasis on short distances by the classical MDS computation. PDM firstly approximates the distance from the unknown nodes to the anchors, signal variation greatly influences the accuracy in this step. Then when PDM use triangulation in the second step, the errors in the distance are amplified. Other triangulation or muti-lateration methods accumulate the errors when the estimated nodes are set to be anchors for next iterations. IRLS using the iterative surrogate method does not accumulate the errors, neither have inherent emphasis on special distances. Therefore, IRLS is not sensitive to the signal variations.

Robustness does not only mean being robust to the signal variations, but also means the adaptation to the loss and addition of nodes. If an algorithm is robust, the accuracy should not decrease dramatically when some nodes fail randomly in the network. From the steps of IRLS, it is clear that if one or more nodes are dead, the result will not change much. This is because such situation can be considered as a decrease of the initial nodes.

The computation complex of MDS is low. Compared with MDS, IRLS is much slower. From a simulation using MATLAB on a computer with Intel Core 2 @ CPU 2.66GHz, RAM 2GB, IRLS costs comparable time with SMACOF. It is well-known that sensor network positioning is a NP-Hard problem, which has heavy computation cost. MDS (classical MDS) uses SVD as the core step. So the computation complex is $O(n^3)$, while n is the number of the nodes. IRLS as well as SMACOF, use the iteration method. The computation complex depends on the iteration time. Even the computation complex of iteration methods is always hundreds times higher than SVD, it is still acceptable from Fig. 15 and Fig. 16.

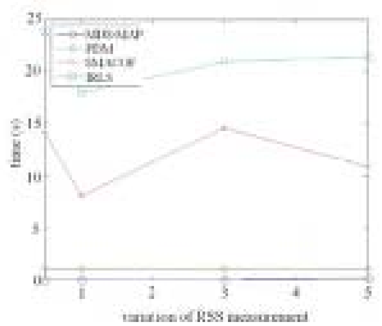

Fig. 15 Time-used in 100-node network

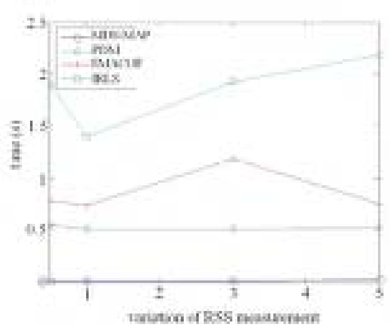

Fig. 16 Time-used in 50-node network

VI. Conclusion

A new algorithm suitable for sensor network localization based on RSS measurement has been proposed. RSS positioning utilizes the received signal strength (RSS) as a distance measurement between a pair of nodes. However, current algorithms would simply translate the RSS measurement directly into distance measurement, and ignores the information embedded in the variation of RSS. Moreover, current algorithms rarely have good performance under large variations of RSS measurement. In this paper, a new target function that is based on signal maximum likelihood (SML) on RSS measurement has been developed. The algorithm that tackles the new target function has been shown to be more accurate than the current algorithms.

Different from other algorithms, the proposed algorithm that tackles the SML is robust to large variation of RSS measurement. Inspired by the SMACOF method, an iterative algorithm called Iteratively Reweighted Least Squares technique (IRLS) has been developed, which utilizes the iterative surrogate idea. With the experience on many simulations, the iteration times for the two levels of loop in IRLS are properly chosen. The choice of the three anchors can also help to improve the accuracy. A comparison has also been carried out between IRLS and the current algorithms such as MDS-MAP, PDM, and SMACOF, which are all based on distance measurement, and not on RSS measurement. The simulation of the centralized version of IRLS has shown that it has better accuracy than all the current methods. The computation complex of IRLS is comparable with the SMACOF method.

To summarize, the IRLS method which is based on RSS positioning has provided a more accurate and robust alternative for localization in a sensor network. In future work, the IRLS method can be extended for large scale network, and a distributed version of IRLS will be developed.

References

[1] T. Eren, Goldenberg, D., Whiteley, W., Yang, Y. R., Morse, A., Anderson, B. and Belhumeur, "Rigidity, computation, and randomization in network localization," in IEEE INFOCOM 2004, pp. 2673-2684.

[2] L. Doherty, K. S. J. pister, and L. El Ghaoui, "Convex position estimation in wireless sensor networks," in INFOCOM 2001. Twentieth Annual Joint Conference of the IEEE Computer and Communications Societies. Proceedings. IEEE, 2001, pp. 1655-1663 vol.3.

[3] L. Hyuk and J. C. Hou, "Localization for anisotropic sensor networks," in INFOCOM 2005. 24th Annual Joint Conference of the IEEE Computer and Communications Societies. Proceedings IEEE, 2005, pp. 138-149 vol. 1.

[4] W. Chengqun, C. Jiming, S. Youxian, and S. Xuemin, "Wireless Sensor Networks Localization with Isomap," in Communications, 2009. ICC '09. IEEE International Conference on, 2009, pp. 1-5.

[5] N. Patwari and A. O. Hero, III, "Manifold learning algorithms for localization in wireless sensor networks," in Acoustics, Speech, and Signal Processing, 2004. Proceedings. (ICASSP '04). IEEE International Conference on, 2004, pp. iii-857-60 vol.3.

[6] Y. Shang, W. Ruml, Y. Zhang, and M. P. J. Fromherz, "Localization from mere connectivity," in Proceedings of the 4th ACM international symposium on Mobile ad hoc networking Annapolis, Maryland, USA: ACM, 2003.

[7] "http://en.wikipedia.org/wiki/Multidimensional_scaling."

[8] J. Xiang and Z. Hongyuan, "Sensor positioning in wireless ad-hoc sensor networks using multidimensional scaling," in INFOCOM 2004. Twenty-third AnnualJoint Conference of the IEEE Computer and Communications Societies, 2004, pp. 2652-2661 vol.4.

[9] "http://www.l-com.com/item.aspx?id=22263.."

[10] T. Rappaport, Wireless Communications: Principles and Practice: Prentice Hall PTR, 2001.

[11] C. Chia-Hung and L. Wanjinn, "Revisiting Relative Location Estimation in Wireless Sensor Networks," in IEEE International Conference on Communications, 2009. ICC '09, 2009, pp. 1-5.

[12] Shashi Phoha, Thomas LaPorta, and C. Griffin, Sensor network operations: Hoboken, N.J. : Wiley ; Piscataway, N.J. : IEEE Press, 2006.