Apply Modified Method of Nonlinear Optimization to Improve Localization accuracy in WSN

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***Abstract*— As is known, location information is playing an important role in most application of WSN, and thus increasing the location accuracy is crucial to this application. However, most of the location refinement algorithms used at present cannot meet the requirement of WSN very well. The linear optimization can achieve small calculating amount at the cost of reducing the positioning accuracy. The traditional unconstrained nonlinear optimization has a better performance in accuracy but always demands large calculating amount. Basing on the principle of unconstrained nonlinear optimization and combining with the characteristics of WSN, this paper proposes two improved novel refinement algorithms: NSSD and MNSQN. Simulation results show that the algorithms proposed in the paper are efficient to relieve the contradiction between calculating amount and localization accuracy by improving the traditional algorithms. The two optimization methods have several advantages: high localization accuracy, relatively low calculating amount, without requiring extra communicational cost, etc.**

Keywords- localization accuracy; WSN; nonlinear optimization.

I. INTRODUCTION AND RELATED WORK

Wireless sensor network applications require that the received data contain the location information. However, a majority of WSN networks use a self-organized way to deploy the sensors. In which the sensors are not able to predict the location by themselves. Therefore, in the network initialization phase, nodes need a process to determine their own position location. In this case, addressing the location of WSN is particularly important with respect to its uncertainty [1].

Considering the characteristics of cheap network nodes and the abundant deployment, the location algorithms need to satisfy the requirements of self-organization, robustness, energy efficiency, distributed computing, etc, [1-2]. Existing distributed location mechanisms of WSN have the similar approach: the deployment of sensor networks requires a certain proportion of special nodes which can access their own specific coordinates (such nodes are often referred to as the 'anchor' or 'beacon'). Through measuring the distance and angle between nodes or using the relative position, network connectivity, we can compute coordinates of nodes to be located by using the location algorithms [3-5].

There has been a series of achievements in improvement of the localization accuracy. And the general algorithms used at present can be divided into two major categories: the optimal solution of linear contradiction equations and optimal solution of nonlinear equations. NICULESCU D [5] uses linear equations to achieve optimal solution through Least Square method, which is a commonly used method at present. As is mentioned in the [6], the use of non-linear equations greatly improves the localization accuracy. The result of the first category is not very satisfactory, usually the location error is also large when the ranging error is relatively large; the second category has a great enhancement in the optimization of location error, but at the same time they has a much larger calculating amount. Because of the limited resources of WSN in operation ability, communication and power, there is still much work to be done to solve these problems.

Based on the principle of non-linear equations' numerical optimization, we make effective modification on the existing optimization algorithm combining with the characteristics of the WSN. We propose two refinement algorithms to improve location precision respectively basing on optimization of the gradient method and optimization of variable metric method. The two algorithms improve not only the computational complexity, but also the accuracy of location and the performance. In this paper, we will discuss related questions in three-dimensional space, so that it's more feasible in practical applications.

The rest of this paper is organized as follows. In Section II we give a formal statement of the problem addressed in this paper. Section III outlines our improved algorithms. In Section IV we present an analysis of our algorithms through simulation. In Section V we conclude our paper with directions for future work.

II. PROBLEM STATEMENT

A. Ranging error

Ranging technology currently used in WSN can not guarantee high accuracy; on the other hand, WSN are generally deployed in an adverse environment, which results in further increase in the range error. As is known, the signal attenuation spreading in the wireless channel is mainly affected by the following factors: multi-path transmission, reflection, non-line-of-sight, antenna gain, etc. [7].

The ranging error is the basic cause for positioning errors. At present, calibration in the range error has got a lot of the achievement, but still ranging error can not be eliminated or

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significantly reduced. Therefore, the first problem of the positioning error arises from the ranging error.

B. *Limitation of Maximum Likelihood Estimation*

When the node to be located (x, y, z) receives location information from n beacons nodes: (x_1, y_1, z_1), (x_2, y_2, z_2) ... ... (x_n, y_n, z_n); the distance between beacons and the node to be located are: d_1, d_2, d_3 ... ... d_n. The process of using Maximum Likelihood Estimation method (also called Least Squares method) to solve this problem is as the following [8]:

$$\begin{cases} (x_1 - x)^2 + (y_1 - y)^2 + (z_1 - z)^2 = d_1^2 \\ \cdots\cdots\cdots\cdots\cdots\cdots \\ (x_n - x)^2 + (y_n - y)^2 + (z_n - z)^2 = d_n^2 \end{cases} \quad \text{-----} (1)$$

Each equation in formula (1) subtracts the final equation, through which we can obtain linear equations, and the matrix form is: AX = B.

$$A = \begin{pmatrix} 2(x_n - x_1) & 2(y_n - y_1) & 2(z_n - z_1) \\ \cdots\cdots & \cdots\cdots & \cdots\cdots \\ 2(x_n - x_{n-1}) & 2(y_n - y_{n-1}) & 2(z_n - z_{n-1}) \end{pmatrix}$$

$X=(x, y, z)^T$;

$$B = \begin{pmatrix} d_1^2 - d_n^2 - x_1^2 - y_1^2 - z_1^2 + x_n^2 + y_n^2 + z_n^2 \\ \cdots\cdots\cdots\cdots \\ d_{n-1}^2 - d_n^2 - x_{n-1}^2 - y_{n-1}^2 - z_{n-1}^2 + x_n^2 + y_n^2 + z_n^2 \end{pmatrix}$$

By maximum likelihood estimation we can obtain: $X=(A^TA)^{-1}A^TB$. Least Squares Solution simplifies the process of solving nonlinear equations, but it may sacrifice the accuracy. The reasons are: the solution of AX=B is the minimal solution of mean-square error $\min\{\| AX=B \|_2^2\}$ (‖★‖ denotes Matrix norm). And the error of solutions is dependent on the error of the *n*th equation, the usually improvement is using one-dimensional search to get the equation in which d_i is smallest. We can use this equation as the *n*th equation to implement the linear transformation above. After this improvement, the positioning error has improved to some degree [10]. On the whole, through Maximum Likelihood Estimation method we can get better computing complexity at the cost of reducing the positioning accuracy. Fig. 1 presents the location error using Maximum Likelihood Estimation.

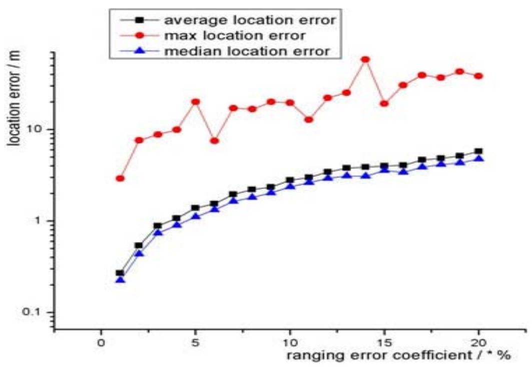

Figure 1. Location error using MLE

C. *Defect of the traditional optimization of unconstrained nonlinear equation*

Expanding $f(X_k)$ near the point X_k in Taylor series we can get:

$$f(X) = f(X_K) + (X - X_K)^T \nabla f(X_K) + \frac{1}{2}(X - X_K)^T H(X_K)(X - X_K) + o\left(\|X - X_K\|^2\right) \cdots\cdots (4)$$

$$\nabla f(X) = \left(\frac{\partial f}{\partial x_1}, \frac{\partial f}{\partial x_2}, \cdots, \frac{\partial f}{\partial x_i}, \cdots, \frac{\partial f}{\partial x_n}\right) T \cdots\cdots (5)$$

$$H(X) = \begin{pmatrix} \frac{\partial^2 f(x)}{\partial x_1^2} & \frac{\partial^2 f(x)}{\partial x_1 \partial x_2} & \cdots & \frac{\partial^2 f(x)}{\partial x_1 \partial x_n} \\ \cdots & \cdots & \cdots & \cdots \\ \frac{\partial^2 f(x)}{\partial x_n \partial x_1} & \frac{\partial^2 f(x)}{\partial x_n \partial x_2} & \cdots & \frac{\partial^2 f(x)}{\partial x_n^2} \end{pmatrix} \text{called } f(X)\text{'s Hessematrix in} X_K \cdots\cdots (6)$$

If we denote $X\text{-}X_k = \lambda P_k$; $X_{k+1}\text{-}X_k = \lambda_k P_k$; then, so long as p_k satisfies: $P_K^T \nabla f(X_K) < 0 \cdots \cdots (7)$

When λ_k is small enough and let $X_{k+1} = X_k + \lambda_k P_k$, then $f(X_{k+1}) < f(X_k)$ [11], thus achieve the numerical optimization.

Apply Unconstrained Nonlinear Optimization to solve the location problem of WSN. First of all, we obtain a set of equations:

$$\begin{cases} \sqrt{(x_1 - x)^2 + (y_1 - y)^2 + (z_1 - z)^2} - d_1 = f_1 \\ \cdots\cdots\cdots\cdots\cdots\cdots\cdots \\ \sqrt{(x_n - x)^2 + (y_n - y)^2 + (z_n - z)^2} - d_n = f_n \end{cases} \cdots\cdots (8)$$

$$F(x, y, z, d_1, d_2, \cdots, d_n) = f_1^2 + f_2^2 + \cdots f_n^2 \sum_{i=1}^{n} f^2{}_i(x, y, z, d_i) \cdots\cdots (9)$$

The minimum value of formula (9) is the optimal solution of formula (8). This method modifies the conspicuous flaw of Maximum Likelihood Estimation (as introduced above).

1) In the formula (7), if $P_k = -\nabla f(x_k)$, then the iterative method constructed in this way is called as gradient method, also known as Steepest Descent method. A relatively practical algorithm of using Steepest Descent method for Unconstrained Optimization problem is STDE algorithm [9], concrete steps are as follows:
   a) *The output of Least Squares assign to $x^{(0)}$; $x^{(0)}$ => x; define ε (permissible error)*
   b) *If | |f(X) | | ≤ ε then output x; algorithm ends.*
   c) *[one-dimensional optimization] search t^*, so that $f(x, t^* \nabla f(x)) = \min_{t>0}(f(x, t \nabla f(x)))$*
   d) *$X - t^* \nabla f(x)$ => X.*
   e) *Go to 2.*

We can see that the gradient method has the following two aspects that need to be improved:

   a) It has not got rid of the local expansion of f(x) yet .
   b) In the iterative process from X_k to X_{k+1}, it still uses the one-dimensional search though the P_k has been obtained, which calls the computing process of f(X) for too many times.

2) In the formula (7), if $P_k = -\mathbf{H}^{-1}(X_k)\nabla f(X_k)$, then the iterative method constructed in this way is called Newton algorithm, also known as Variable Metric method. Among of the methods that can solve Unconstrained Nonlinear Optimization problem, variable metric method

especially Quasi-Newton is considered to be the most effective method. However, there are three aspects to be improved in traditional variable metric algorithm:

a) Algorithm must calculate the n-order matrix H_k, resulting in larger computation; at the same time, it is requisite to store matrix H_k, resulting in larger storage capacity.
b) In order to maintain high-speed convergence, the condition of $\lambda_k=1$ is very important, but under certain circumstances even though $\lambda_k=1$, it still can not guarantee that $f(X_{k+1})<f(X_k)$ will always be tenable when $X_{k+1}=X_k+\lambda_k P_k$.
c) In the iterative process from X_k to X_{k+1}, it still uses the one-dimensional search though the P_k has been obtained, which calls the computing process of f(X) too many times.

III. LOCATION ALGORITHMS BASED ON UNCONSTRAINED NONLINEAR OPTIMIZATION

We have analyzed deficiency of location algorithms used at present in Part Ⅱ. Based on priori knowledge, in this part, we will combine principle of unconstrained non-linear optimization with the positioning of WSN, and propose two position refinement algorithms, so as to enhance self-localization accuracy of the node to be located.

Meanwhile, the optimization problem of unconstrained nonlinear equations has a relatively high requirement that the initial value $x^{(0)}$ should be relatively close to the optimal point x^*, otherwise it will not be able to converge to the optimal point x^*. Therefore a reasonable initial value is very important, for it will affect rationality of the final result. A theoretically possible method is to make the export value of least-squares method as the initial value of gradient method, the concrete proof demonstration of which is in [9].

A. Applying NSSD algorithm (No-Search Steepest Descent) to enhance positioning precision

A big defect of traditional Steepest Descent method is that iterative process calls one-dimensional search for the optimization of λ_k though the P_k has been obtained, which calls the process of computing f(X) too many times and increases the complexity of computing. It is necessary to try to avoid a large amount of computing in the WSN whose power and computing resources are limited.

The descent direction of Steepest Descent method is the negative gradient direction $-\nabla f(x^{(i)})$ and is the fastest decline direction as well. When the distance between optimal value and the iterative numericals is relatively far, the rate of convergence is very quick. In engineering applications rather than rigorous mathematical theory studies, after a few steps of this rapid convergence process we can obtain relatively optimal solution which meets the requirement of engineering applications such as the localization of WSN.

In the theoretical research of unconstrained nonlinear optimization, we can conclude that the iteration formula will be possibly convergent when $0<\lambda_k\leq1$. Especially for Variable Metric optimization method, any value in this interval will make the result converge in theory. Meanwhile, it does not require very high accuracy due to the specificity of the application, so in the fast convergence of iterative process mentioned above, λ_k exists an optimal range of values ($c_1 \leq \lambda_k \leq c_2$) ,as we know that steepest descent and Newton method are descent methods, so this phenomenon may also appear in the Newton method. Fig. 2 demonstrates this conclusion. (The beacon number is six). In the graph, we can see that any value in this interval ($0<\lambda_k\leq1$) will make the iteration formula converge for Newton method. And λ_k exists an optimal range of values ($0.14 \leq \lambda_k \leq 0.16$) when use the steepest descent method. But when the $\lambda_k>0.25$, the result of the iteration formula is not convergent and increases very fast. But as is known, in most of the cases, the ranging error coefficient is less than 0.25. So we can reasonably set λ_k to be a constant satisfies $0.14 \leq \lambda_k \leq 0.16$. (in fig. 2, number of beacons is 6)

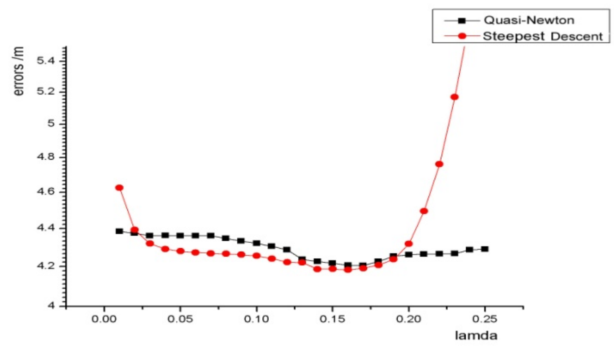

Figure 2. The relation between λ_k and location error

Based on the conclusions above, we can improve the Steepest Descent method and Quasi-Newton method so as to avoid the one-dimension search and modify the traditional steepest descent method's flaw proposed by paragraphs above.

Defined by formula (8) and formula (9), multi-dimension function $f(X) = f(x, y, z, d_1, d_2, \cdots d_n)$, the concrete steps using NSSD (no-search steepest descent) method is as follows: (all of the symbol ||*|| in this paper is defined as $||X||=|x_1|+|x_2|+\ldots\ldots|x_n|$) :

1) *The output of the least square(x,y,z)+ distance array $(d_1,d_2,\ldots,d_n) \Rightarrow x^{(0)} \Rightarrow x$; define ε (allowable error);*
2) *If $||f(x)|| \leq \varepsilon$ then output x; algorithm ends.*
3) *t^*= optimal λ_k (constant); $x - t^* \nabla f(x) \Rightarrow x$;*
4) *go to 2*

We can conclude by analyzing simulation data that the NSSD method is an excellent method to improve positioning precision.

B. Applying MNSQN (memoryless and no-search quasi-Newton) to improve positioning precision

The traditional quasi-Newton method [11] must get H_k in order to obtain H_{k+1}, for this purpose it musts spend n^2 of the memory cell. It's not the ideal method to solve the problem of large scale in the sensors that have relatively small memory. What's more, the biggest defect of the traditional Quasi-

Newton method is the computational complexity. It's unreasonable for the applying in small machines which have limited resources, such as sensors.

The computational complexity of the traditional quasi-Newton method is the main cause that incumbers its application in WSN. The main reason for the computational complexity is the computation of Hessen matrix; so if we can overcome this difficulty, the modified quasi-Newton method can be used in WSN to meet the requirement of it.

$P_k = -\mathbf{H}^{-1}(X_k)\nabla f(X_k) \Rightarrow H_k^{-1}P_k = -\nabla f(X_k)$, then use a special matrix B_k to replace H_k^{-1}, then $B_kP_k = -\nabla f(X_k)$, in the iterative process we can confirm B_{k+1} which satisfy:

$$B_{k+1}\Delta x_k = y_k \quad \cdots\cdots (10)$$

In which, $\Delta x_k = x_{k+1} - x_k$; $y_k = \nabla f_{k+1} - \nabla f_k$

We can easily know from the iterative formula that the generation of B_{k+1} need not have relationship with B_k, as long as we generate B_{k+1} which obeys secant relation, we can set up an effective iterative method. The following is how to generate B_{k+1}, so that it obeys the secant relation:

$l_k=\|y_k\|\Delta x_k+\|\Delta x_k\|y_k/\|(\|y_k\|\Delta x_k+\|\Delta x_k\|y_k)\|$,
$u_k=(\|\Delta x_k\|l_k-\Delta x_k)/\|(\|\Delta x_k\|l_k-\Delta x_k)\|=(u_1^{(k)},u_2^{(k)},\ldots,u_n^{(k)})^T$
$v_k=(\|y_k\|l_k-\Delta x_k)/\|(\|y_k\|l_k-\Delta x_k)\|=(v_1^{(k)},v_2^{(k)},\ldots,v_n^{(k)})^T$

$$B_{k+1} = \|y_k\| H_2^{(k)} H_1^{(k)} / \|\Delta x_k\| \cdots\cdots (11)$$

$$P_k = -\|\Delta x_k\| H_2^{(k)} H_1^{(k)} / \|\Delta y_k\| \cdots\cdots (12)$$

Formula (11) must obey the secant relation [11], formula (12) reduces the computational complexity of $\mathbf{p_k}$, so it solves the problems brought by Hesse matrix. The improved MNSQN method avoid the matrix inverse、need not to store a large number of intermediate variables matrix and is easy to compute the solution**.** The multi-dimensional function is based on formula (8) and formula (9). The steps of using MNSQN algorithm are as follows:

1) 0=>k ;
2) $g_k=\nabla f(x_k)$
3) if $\|g_k\|<\varepsilon$, then $x= x_k$, stop iteration; else go to 4.
4) when k=0 , $p_k = g_k$;
   when$k\neq 0$

$$p^k = -(\|\Delta x_k\|/\|y_k\|)(g_1^{(k)} - 2v_1^{(k)}\sum_{i=1}^{n} v_i^{(k)}g_i^{(k)}$$
$$-2u_1^{(k)}\sum_{i=1}^{n}(u_l^{(k)}(g_1^{(k)} - 2v_l^{(k)}\sum_{i=1}^{n} v_i^{(k)}g_i^{(k)})))\cdots$$
$$g_n^{(k)} - 2v_n^{(k)}\sum_{i=1}^{n} v_i^{(k)}g_i^{(k)}$$
$$-2u_n^{(k)}\sum_{l=1}^{n} u_l^{(k)}(g_l^{(k)} - 2v_l^{(k)}\sum_{i=1}^{n} v_i^{(k)}g_i^{(k)}))^T$$

5) λ_k= select one constant in the set of (0,1];
   $x_{k+1}=x_k+ \lambda_k P_k$;
6) Calculating $\Delta x_k=x_{k+1}-x_k$;
   $g_{k+1}=\nabla f(x_{k+1})=(g_1^{(k+1)},g_2^{(k+1)},\ldots,g_n^{(k+1)})^T$; $y_k=g_{k+1} - g_k$;
   $l_k=\|y_k\|\Delta x_k+\|\Delta x_k\|y_k/\|(\|y_k\|\Delta x_k+\|\Delta x_k\|y_k)\|$,
   $u_k=(\|\Delta x_k\|l_k-\Delta x_k)/\|(\|\Delta x_k\|l_k-\Delta x_k)\|=(u_1^{(k)},u_2^{(k)},\ldots,u_n^{(k)})^T$
   $v_k=(\|y_k\|l_k-\Delta x_k)/\|(\|y_k\|l_k-\Delta x_k)\|=(v_1^{(k)},v_2^{(k)},\ldots,v_n^{(k)})^T$;
7) k+1=>k, go to 3)

IV. SIMULATION AND ANALYSIS

In the simulation experiments, we evenly deploy 7 nodes in a 40m *40m*40m target field on the OMNET++ platform. There are six beacons and one sensor node to be located in the target field. The node S is located at the center of this target field and beacons are randomly located in the transmission range of S. We assume the maximum transmission range of all nodes is R=20m. The ranging error obeys normal distribution N (0, δ^2) [12], δ is set as the variable which equals measurement error d_i multiplies a constant c ($\delta= d_i * c$). In this section, we compare the performances of improved algorithms with the conventional algorithms' and analyse the results.

1) Comparison of Maximum Likelihood Estimation, NSSD and MNSQN in positioning error, as fig. 3 and fig. 4 demonstrate (in fig. 3, number of beacons is 6).

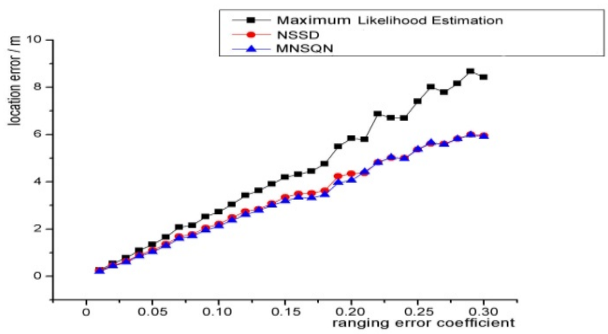

Figure 3. Comparison of MLE, NSSD, and MNSQN in accuracy

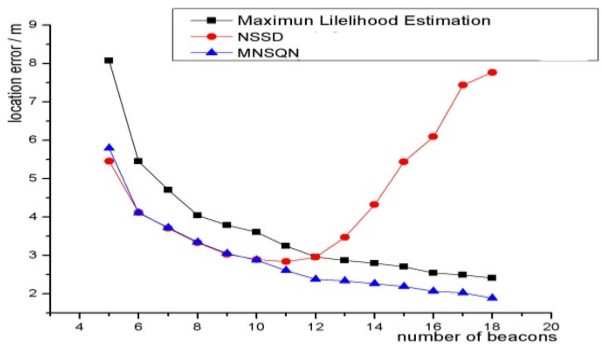

Figure 4. Comparison of MLE, NSSD, and MNSQN in complexity

From the fig. 3, we can see that the localization accuracy of NSSD and MNSQN are significantly better than Maximum Likelihood Estimation. Especially when ranging error is relatively large, position precision can be improved more than 26% using NSSD or MNSQN, such as when ranging error coefficient is 0.25, localization accuracy is improved by 28.5%.

Fig. 4 shows that the localization accuracy of NSSD and MNSQN are significantly better than Maximum Likelihood Estimation when number of beacons is less than 11. However, the location error increases very fast when the number is more than 11. This phenomenon validates the conclusion that the λ_k

is local optimum for Steepest Descent algorithms. When the number of the beacons is more than 14, the value of λ_k satisfies $0.14 \le \lambda_k \le 0.16$ is not reasonable any more. But as is known, the case that the number of beacons within the communication range of sensor S is more than 14 is rare because of the cost of deployment. Moreover, when number of beacons is more than 14, we can take measures to change the value of λ_k easily. So the improved algorithm is reasonable and robust in the practical application.

2) In this paper, we propose two location refinement algorithms—NSSD and MNSQN--basing on the traditional algorithms and combining the characteristics of applications in WSN, the comparison of performance between traditional algorithms and improved ones is as follows:
   a) Fig. 5 and fig. 6 show the comparison of traditional Steepest Descent and NSSD (in fig. 5, number of beacons is 6).

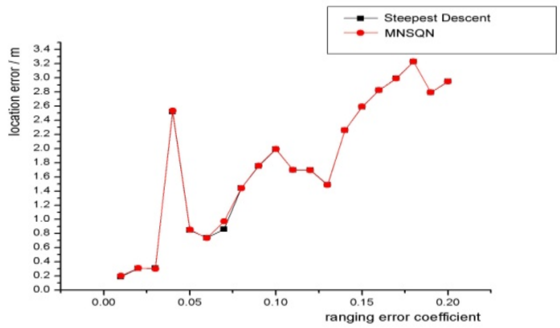

Figure 5. Comparison of traditional SD and NSSD in accuracy

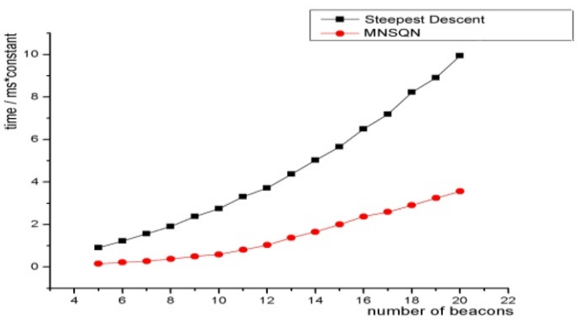

Figure 6. Comparison of traditional SD and NSSD in complexity

As fig. 5 shows, the improved algorithm NSSD does not lower the positioning precision. That is to say it is possible to maintain precision without one-dimensional search. Meanwhile, we can see from Fig. 6 that algorithm NSSD has a significant lower computation complexity, especially when number of the beacons within communication range increases, this advantage can obviously save the resource for positioning computation.

   b) Fig. 7 and fig. 8 show the comparison of traditional Quasi-Newton and MNSQN (in Fig. 7, number of beacons is 6).

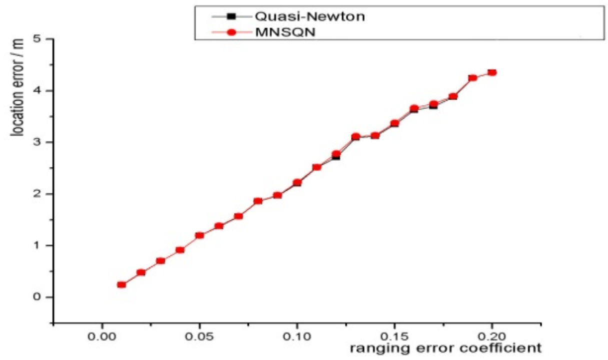

Figure 7. Comparison of traditional Quasi-Newton and MNSQN in accuracy

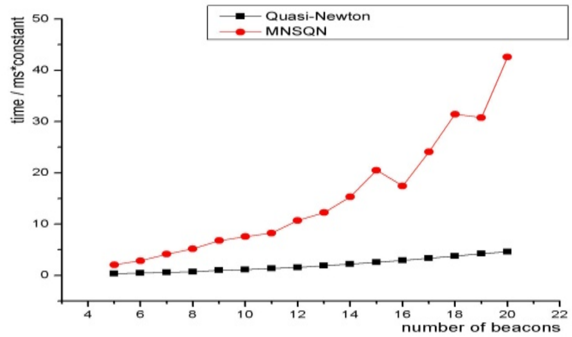

Figure 8. Comparison of traditional Quasi-Newton and MNSQN in complexity

As fig. 7 shows, although the improved algorithm does not store the Hessen matrix and optimization of one-dimensional search, it can maintain the precision. Meanwhile, from Fig.ure 8 we can see that the computational complexity of improved algorithm is significantly reduced. Obviously, the improved Quasi-Newton (MNSQN) is more suitable for the application of localization of WSN.

   c) Fig. 9 and Fig. 10 show the comparison of NSSD and MNSQN (in Fig. 9, number of beacons is 6).

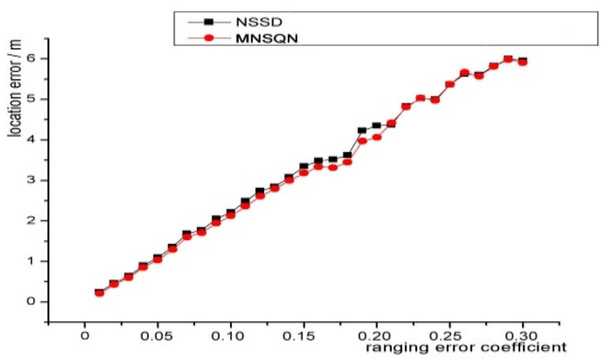

Figure 9. Comparison of NSSD and MNSQN in accuracy

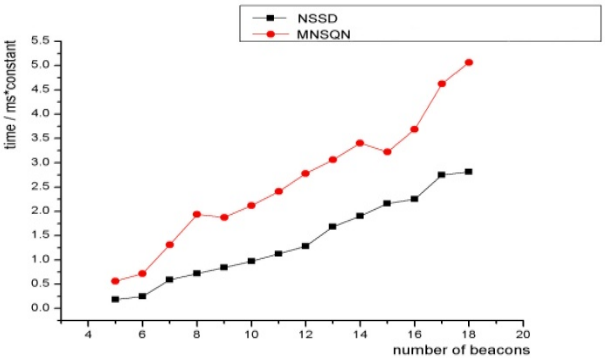

Figure 10. Comparison of NSSD and MNSQN in complexity

Fig. 9 and fig. 10 illustrate comparison of the performance between gradient-based method and variable metric method. The two methods have similar localization accuracy, as a whole, MNSQN has a little advantage; but fig. 10 shows that NSSD has a little lower computational complexity. So at the actual applications of localization in WSN, the two algorithms are both ideal to improve the localization accuracy.

V. Conclusion

In this paper, we improve the traditional optimization algorithm and propose two accurate positioning algorithms. Basically, we analyze the unconstrained nonlinear optimization theory and the feasibility of its application to improve positioning accuracy, combining the characteristics of WSN. The algorithms are improved greatly on performance, and simulation shows the positioning accuracy is increased significantly as well. Without reducing the positioning accuracy, NSSD and MNSQN have much lower computation complexity than the traditional algorithms, which is very important for WSN to save the limited resource.

In our future work, we will improve the robustness of algorithms on the case of more complex location errors on the basis of this. For example, how to get an optimal solution when there is extremely inaccurate individual ranging value.

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