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A Selective Beacon Node 3D Location Estimation based on RSSI for Wireless Sensor Network

[1,2]Xiaoyong Yan, [1]Huanyan Qian and [1,2]Jiming Yu
[1]School of Computer Science and Technology, Nanjing University of Science and Technology, Jiangsu, Nanjing, 210094, China
[2]College of Information Technology, Jingling Institute of Technology, Jiangsu, Nanjing, 211169, China

Abstract: The harsh radio propagation environments and relative geometry of the beacon nodes has always been obstacles to improve the localization accuracy in wireless sensor network. Although, there has been many researches invented to solve these problems and some of them has significantly improved the localization accuracy; they were impeded to provide enough high accuracy for insufficiently exploiting nodes deployed around the actual situation, as well as the beacon node topology and transmission signal characteristics. In this study, localization algorithm first analyze the characteristics and types of ranging error and develop a new novel filter model: median-based weighing which the weighed means instead of original data. Localization algorithm then analyze the quality of tetrahedral mesh constituted by four beacon nodes and propose a novel localization mechanism which only select the beacon nodes with good topology quality to estimate the of unknown node. The simulation results show that the proposed algorithm has better localization performance in the localization precision and stability than the basic location estimation algorithm and some existing improved.

Key words: Wireless sensor network, 3D-localization, received signal strength, robust estimation, tetrahedral mesh

INTRODUCTION

Wireless Sensor Network (WSN) (Akyildiz *et al*., 2002) refers to a sort of wireless network comprised by large amounts of static or mobile sensor network nodes in forms of self-organization and multi-hop. It has attracted more and more attentions in many fields such as military affairs, environment monitoring and protection, urban traffic and medical treatment. In many application problems related with sensor network, location information of nodes is of great importance to the monitoring activity of the whole network which plays a critical role in many application. The research of sensor localization technique, as one of the fundamental technologies of WSN, is very important to the network activities (Mao *et al*., 2007a). Generally, nodes' location information can be acquired by adding GPS on nodes. In most applications, however, sensor nodes are resource-constrained (e.g., low-power, low-memory, low operational ability) and have limited communication ranges and only applicable under outdoor and open-sided circumstance. Besides, GPS also needs stable base installations. As for this, an economic and feasible approach is to deploy GPS just for a small number of sensors (also called known sensors or beacons) in the deploying area (Bruck *et al*., 2009). For the rest of the nodes, their physical locations can only be calculated with a certain localization technique. After several years' development, researchers have proposed many node localization algorithms. However, the majority of localization techniques proposed in the literature are designed and evaluated considering only two-dimension (2D) applications where the sensing area is assumed flat. In most practical circumstances, sensor networks are usually deployed in complex three-dimension (3D) terrains such as a surveillance network deployed in a mountainous battlefield, a structural monitoring network mounted on a listed building or a surveillance network deployed in a mountainous battlefield and so forth. The 3D node localization problem in WSN poses new challenges for the localization scheme design (Shi *et al*., 2009). Now-a-days, scholars have obtained better experimental results on 3D Localization in Wireless Sensor Networks and also have made some groping researches by using the results on Tikhonov regularization (Wang *et al*., 2010) or Delaunay

Corresponding Author: Huanyan Qian, School of Computer Science and Technology, Nanjing University of Science and Technology, Jiangsu, Nanjing, 210094, China

triangulation (Shi *et al*., 2009) to some 3D Localization. However, there still exists some problems for 3D Localization to be resolved, such as node deployment environment, the impact of ranging error, etc.

Generally, the localization process can be simply divided into two phases (Wan *et al*., 2009). At the first phase, sensor nodes communicate with neighbors to estimate distance between pairs of devices. At the second phase, a localization method is used based on previous estimated distance, sensor nodes can finally estimate their physical locations in the form of coordinates. "Zero error" is the eternal pursuit of localization algorithm. Owing to the limited computing capacity of sensor and complexity in the network environment, each stage would generate some errors that have significant influence on the final coordinate estimation (Wan *et al*., 2009).

The most popular ranging techniques (Liu *et al*., 2010) in wireless sensor networks are RSSI (Received Signal Strength Indicator), ToA/TDoA (Time of Arrival/Time Difference of Arrival) and AOA (Angle of Arrival). RSSI-based localization (Mao *et al*., 2007b) does not require any special or sophisticated hardware and it is available in most of the standard wireless devices. Moreover, RSSI-based localization is unlikely to significantly impact on local power consumption, sensor size and thus cost and for this reason it has received considerable interest in the recent literature. Unfortunately, real measurement of RSSI can be highly inaccurate due to variability caused by multipath effects, blocking and ambient noise interference and it cannot be treated as a good distance estimate (Zheng and Jamalipour, 2009). In recent years, it has become a new research hot spot to make use of robust estimation (Zhao *et al*., 2008) to improve the localization accuracy and algorithm design of localization mechanism. In this study, we focus on wireless sensor networks location estimation using radio frequency based upon signal strengths. We analyze the properties and types of RSSI error on a novel, more stable, robust and simpler estimation to minimize the influence of noise on the RSSI.

With the calculation of distance information acquired at the first step, sensor node can finally estimate their physical locations based on beacon node. Theoretically, more available beacon nodes could lead to more accurate localization result. However, in fact, the geometric distribution of beacon nodes, as well as the geometric structure formed between beacon nodes and unknown nodes will largely affect the localization result of unknown nodes. Ordinary RSSI-based algorithm relies much on topology of beacon nodes (Zheng and Jamalipour, 2009). For this reason, more beacon nodes may not necessarily lead to higher localization precision. In this study, novel algorithm propose a selective beacon node 3D location estimation based on RSSI (SN3DLE-RSSI)and our algorithm makes unknown nodes able to choose some beacons from their neighbor beacons which guarantees more precision to execute localization process and improve the localization precision.

TWO MAIN ERRORS

Error analysis at measurement stage: At the first stage of node positioning, namely, measurement stage, the measured value of RSSI is affected by environmental factors such as the presence of obstacles, multipath and shadowing effects and changes of the signal propagation speed along with changing the surrounding environment. Meanwhile, sensor nodes are generally deployed in complicated environments, in which case they are likely to be affected by factors such as hardware ageing, hostile attacks, environment noise and the lack of power and thus contain more errors in signals got. The experiment results in literatures show that if the errors are not proposed, the positioning errors of over 30% may be caused in the case of 10% ranging errors (Mao and Fidan, 2009). All of these bring difficulties to practical application.

Generally, to avoid the influence caused by single RSSI measurement errors when using an RSSI for ranging estimation, a mean value smoothing method (Karagiannis *et al*., 2012) is generally used to process errors, that is to say, first collect a group including N RSSI signals from nodes and then average the group of data. The method can balance instantaneity and accuracy by adjusting the number of N and effectively solve the randomness of measured data in the case of a big n but apparently, the computing amount will increase accordingly. In addition to this, it can be seen that the RSSI data generally contain two kinds of errors with different natures. One kind is called random errors which are produced due to factors such as internal device noise or A/D quantizing noise and are in large number and have small margins. Such errors can be removed easily by mean value smoothing method. The other is called gross errors (often called outliers), referring to the stray data which are different from others obviously. Such errors are mutational disturbances caused by accidental events in external environment (such as the movement of human or other movable objects between nodes), strong noise or hostile attacks. They have big margins but are in small number. Some statists have pointed out in production practice and scientific experiments that the outliers account for about 1-10% of measured data (Huber and Ronchetti, 2011). The mean value smoothing method can effectively resist the influence of a large number of small errors but when there are outliers in data, measured data's accuracy reduces greatly. It is because measured data form a distribution set instead of complying with the normal distribution due to the appearance of outliers. For such data containing various distributions, it is hard to get the optimal estimation through traditional optimal estimation. Huber and Ronchetti (2011) has made a statistical analysis using data containing different numbers of outliers and proved that the mean value estimation method was unavailable in the case that 1000 data contain 2 outliers. It indicates that outliers generally bring negative effects and then affect the conclusion. Therefore, it is more and more important to seek for effective strategies against outliers. According to 3-sigma principle of probability, that is, there must be small-probability events in a group of RSSI signals received by one node in the same position, some scholars (Zhang *et al*., 2008) selected RSSI values in high probability region and got their geometric mean. The method reduces the influence of some small-probability and big-disturbance events on the overall measurement and increases the accuracy of positioning information. But it is under the assumption that the proposed data conform to a normal distribution and the ratio of outliers are not high, so in practical conditions using 3-sigma method to smooth outliers can not get an ideal result. Li *et al*. (2008) made estimation to unknown nodes using Least Median Square (LMS). The LMS estimation adopted combines least square and median, of which the median used has high robustness and fault-tolerant capability and is the maximum likelihood estimation of Laplace distribution. In term of overall error-resistance capability, median is the estimation with the strongest error-resistance capability. Theoretically, the test sample contains 50% outliers, yet the estimated value got through median is still reliable. But LMS method sees the data containing outliers as garbage and simply eliminates them. However, RSSI data containing gross errors may be the result of inherent signal data variance and are not necessarily caused by execution errors. Simply removing the data may cause a loss of important hidden information. Of course, stray data can not be treated as normal data. A reasonable practice is giving them corresponding weights, respectively according to their distribution probabilities, to reduce the influence of abnormal data. Inspired by the strong error-resistance capability of median, the study recombines signal sequences got using a new median-based weighting method at positioning and ranging stage.

Error analysis at computing stage: After getting the distances between an unknown node and its close beacon nodes, location estimation can be made using a multilateral method or ordinary least square technique. In general, the more beacon nodes are chosen by the unknown node, the more accurate the estimated position is. But, in fact, the topology of beacon nodes and the topological structure formed between beacon nodes and the unknown node will greatly affect unknown node's positioning result. At a minimum, three non-collinear beacon nodes are required to define a global coordinate system in two dimensions. If three dimensional coordinates are required, then at least four non-coplanar beacons are required in return. Some research indicate that the maximum errors caused by improper topological structure in two-dimensional space can be 200% (Tian *et al*., 2007). It is easy to know that when making three-dimensional positioning using four beacon nodes, the positioning result will form a tetrahedron centering on the unknown node. Similar as the two-dimensional space, the quality of the tetrahedron mesh formed by four beacon nodes greatly affects the final position estimation. As shown in Fig. 1, if the geometric distributions of beacon nodes L_1, L_2, L_3, L_4 are completely coplanar, when using the traditional position estimation method, unknown node A's estimated coordinate may be A or A', in which case node A's physical coordinate can not be estimated and the errors will reach 200%.

In the study, a localization unit is defied as a beacon node group can determine at least one unknown node. Localization in the two-dimensional space needs at least three beacon nodes and the final positioning result is directly affected by the quality of the triangle constituted by positioning units. Sarrate *et al*. (2003) analyzed the triangular grid's quality in literatures. As to the triangle with a big aspect ratio, i.e., the triangle has at least one small angle and its three vertexes are close to be collinear (Fig. 2), there are two types: One type has no short edge

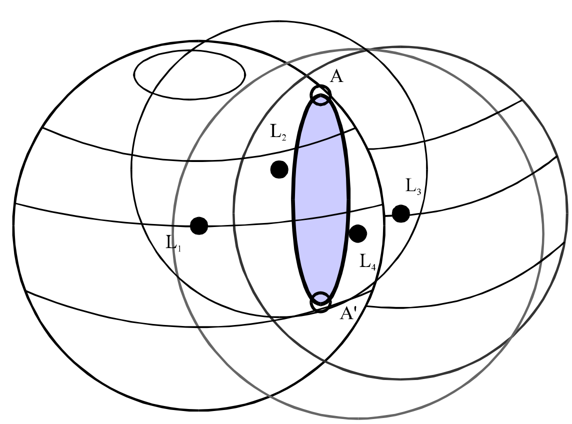

Fig. 1: Four coplanar beacons in three-dimensional space

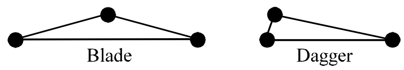

Fig. 2: The poor-quality of localization unit in two-dimensional space

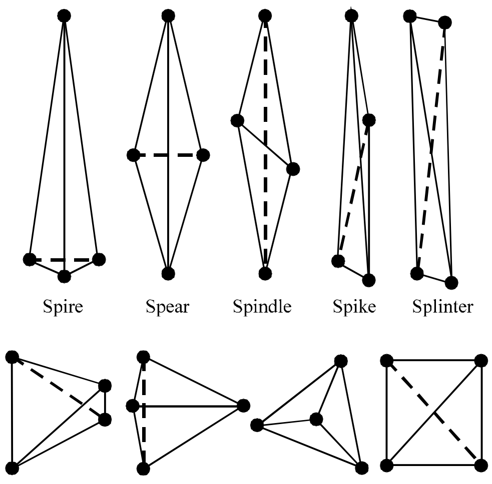

Fig. 3: The poor-quality of localization unit in three-dimensional space

and is called blade; the other type has one short leg and is called dagger. It is also easy for us to know there are six quality measures of a triangle, they are:

$$q_{\alpha\min} = \frac{3\alpha_{\min}}{\pi},\ q_{LL} = \frac{l_{\min}}{l_{\max}},\ q_{ALS} = \frac{4\sqrt{3}A}{l_1^2+l_2^2+l_3^2}$$
$$q_{Rr} = \frac{2r}{R},\ q_{Lr} = \frac{2\sqrt{3}r}{l_{\max}},\ q_{Lh} = \frac{2h_{\min}}{\sqrt{3}l_{\max}} \quad (1)$$

where, α_{min} is the smallest inner angle, l_{min} and l_{max} are the length of the shortest and longest edge, respectively, l_1, l_{21} and l_3 are the length of the three sides of the triangle, A is the area of the triangular element, r is the inradius of a triangle, R is the circumradius of a triangle and h_{min} is the minimum height of the triangle.

While, in the three-dimensional space, a localization unit should be constituted by at least four beacon nodes. Similarly, the quality of tetrahedron mesh constituted by localization units decides the final location estimation result directly. The tetrahedron mesh is generally considered as the expansion of triangle in the three-dimensional space, so the tetrahedron constituted by triangles with a large aspect ratio has poor topology quality. Cheng *et al*. (2000) made detailed study on the tetrahedrons, proposing nine kinds of poor-quality tetrahedron whose structures are shown in Fig. 3.

It can be seen from the Fig. 2 that these tetrahedrons mesh all have triangular grids with a big aspect ratio and these tetrahedrons mesh all have a volume approximating to zero; they all have the characteristic of nearly coplanar four points. It is generally believed that tetrahedron mesh's quality criteria include: the metric will not change in the case of tetrahedron mesh cells' translation, rotation, reflection and equal scaling; the metric unit reaches the maximum in the case of a regular tetrahedron and tends to zero in the case that its volume tends to zero. Basing on the criteria, researchers have proposed many criteria for measurement of which the most common ones include the minimum solid angle θ, radius ratio ρ, coefficient Q and coefficient γ. They are respectively defined as follows:

- Minimum solid angle θ:

$$\theta = \min(\theta_1, \theta_2, \theta_3, \theta_4) \quad (2)$$

where, θ_1 is given by:

$$\sin\left(\frac{\theta_1}{2}\right) = \frac{12V}{\left(\prod_{2\le j<k\le 4}[(l_{1i}+l_{1j})^2 - l_{ij}^2]\right)^{0.5}}$$

θ_2, θ_3, θ_4 can be obtained by rotation of indices.

- Radius ratio ρ:

$$\rho = 3r/R \quad (3)$$

where, r and R are the inradius and circumradius of the tetrahedron mesh, respectively.

- The Q coefficient:

$$Q = C_d \frac{V}{[\sum_{1\le i<j\le 4} l_{ij}]^3} \quad (4)$$

where, the coefficient $C_d = 1832.8208$ is applied so that the highest value of Q (for equilateral element)is equal to 1.

- The γ coefficient:

$$\gamma = \frac{72\sqrt{3}V}{\left[\sum_{1\le i<j\le 4} l_{ij}^2\right]^{1.5}} \quad (5)$$

In above expression, V denotes the volume of tetrahedron mesh with vertexes P_1, P_2, P_3, P_4, l_{ij} represent the length of the edge joining P_i and P_j.

Literatures also demonstrate that the formulas above are equivalent; the formulas all tend to zero in the case that the tetrahedron mesh's volume tends to zero; metric formula value tends to 1 in the case that the tetrahedrons mesh tends to a regular tetrahedron mesh. Considering that the metric criteria approximate to equivalence and taking computation convenience and legibility into account, the study adopted an easily understood radius ratio to measure the quality of topology shape of four beacon nodes in three-dimensional space and set certain threshold values to avoid complete or approximate coplanar situation in positioning.

ELABORATE ON ALGORITHMIC MODEL

Aiming at problems existing in two stages of positioning, SN3DLE-RSS algorithm first eliminates the influence of errors in measured data using a median-based weighting method and then analyzes the topology of beacon nodes and only selects the beacon nodes with good topology quality to estimate the position of unknown node. The algorithm is elaborated later.

Median-based weighing algorithm: The most effective method reducing the influence of outliers is replacing mean value with median. Inspired by this, the study used a statistical media weighing method. First, keep the communication between each pair of nodes for some time and get a certain number of RSSI data; next, find the median of RSSI signal strengths; then, compute the weight of each signal's strength in signal sequence based on the median; finally, multiply each signal by corresponding weight and sum them up and output the result as the RSSI signal between two nodes. The weight should meet the following conditions: (1) the closer the signal value of one point in the sequence to the median of the sequence is, the bigger the weight is. If one point is a RSSI signal containing gross errors, its signal strength has a great difference from the median and thus the weight is small accordingly, (2) In the sequence, there may be some signals close to the median and also containing outliers which may expand stray signals' influence on final output signals. Therefore, a threshold is added to the algorithm. In this case, the weight will be decided by the variance in the case the variance is bigger than the threshold or by the threshold in the case that the threshold is bigger than the variance and (3) Weight normalization. Multiply the signal value of each point in the sequence by corresponding weight and sum them up to get a result as the RSSI signal between two nodes.

A summary of our algorithm is provided as follows:

Step 1: Each beacon node broadcasts its position $Beacon_i\{ID_i, (X_i, Y_i)\}$ through controlled flooding. Nodes in the range of effective communication radius will receive the positional information. The unknown node will get corresponding RSSI signal sequence after some time

Step 2: Find corresponding median Med_{RSSI} in each RSSI signal sequence. First, the RSSI signal sequence $RSSI_1, RSSI_2,..., RSSI_n$ is sorted by value size, that is to say, $RSSI_{(1)} \le RSSI_{(2)} \le RSSI_{(3)} .. \le RSSI_{(n)}$ and the median of signal sequence is expressed as:

$$Med_{RSSI} = \begin{cases} RSSI_{(\frac{n+1}{2})} & , \text{ n is odd} \\ \frac{1}{2}\left(RSSI_{(\frac{n}{2})} + RSSI_{(\frac{n}{2}+1)}\right) & , \text{ n is even} \end{cases} \tag{6}$$

Step 3: Get corresponding weight of each RSSI signal strength value in the sequence. First get d_i, the variance of each RSSI signal value and the median of signal sequence; to avoid the influence of stray signals close to median, add a threshold to the algorithm and the weight is decided by the variance if the variance is bigger than the threshold value or decided by the threshold if the variance is smaller than the threshold. The weight of each RSSI signal in each sequence can be computed according to the following formula:

$$w_i = \frac{\dfrac{1}{1+\max\{T,(RSSI_i - Med_{RSSI})^2\}}}{\sum_{i=1}^{n} \dfrac{1}{1+\max\{T,(RSSI_i - Med_{RSSI})^2\}}} \tag{7}$$

And, the threshold T can be expressed by the following formula:

$$T = \frac{\sum_{i=1}^{n}(RSSI_i - Med_{RSSI})^2}{n} \tag{8}$$

Here, n is the number of sequence; $RSSI_i$ is the ith RSSI signal value in the region. It can be seen that the greater the difference between $RSSI_i$ and Med_{RSSI} is, the smaller the corresponding weighting coefficient is; T changes with the variance of $RSSI_i$ and Med_{RSSI}.

Step 4: Multiply each signal value in the region by corresponding weighing coefficient and output summing result $\sum_{i=1}^{n} w_i \times RSSI_i$ as the RSSI signal value between two nodes. Finally, transform the RSSI signal value into corresponding distance using a lognormal shadow model

Beacon node selection algorithm: After getting the corresponding measuring distance, it is often to use a multilateral method or least square estimation method for location estimation. Presume that (x, y, z) is the coordinate of an unknown node U which can intercommunicate with $n(n\geq 4)$ beacon nodes. Presume that the coordinate of the ith beacon node is (x_i, y_i, z_i) and the distance from node U to beacon node is d_i, so we can get:

$$\begin{cases}(x-x_1)^2+(y-y_1)^2+(z-z_1)^2=d_1^2\\(x-x_2)^2+(y-y_2)^2+(z-z_2)^2=d_2^2\\\vdots\\(x-x_n)^2+(y-y_n)^2+(z-z_n)^2=d_n^2\end{cases},\ n\geq 4 \tag{9}$$

It is easy to transform it into a form of AX = b, with:

$$A=2\times\begin{bmatrix}(x_1-x_n) & (y_1-y_n) & (z_1-z_n\\ \vdots & \vdots & \vdots\\ (x_{n-1}-x_n) & (y_{n-1}-y_n) & (z_{n-1}-z_n)\end{bmatrix} \tag{10}$$

$$b=\begin{bmatrix}x_1^2-x_n^2+y_1^2-y_n^2+z_1^2-z_n^2+d_n^2-d_1^2\\x_2^2-x_n^2+y_2^2-y_n^2+z_2^2-z_n^2+d_n^2-d_2^2\\\vdots\\x_{n-1}^2-x_n^2+y_{n-1}^2-y_1^2+z_{n-1}^2-z_n^2+d_n^2-d_{n-1}^2\end{bmatrix} \tag{11}$$

$$X=\begin{bmatrix}x\\y\\z\end{bmatrix} \tag{12}$$

In real-world applications, the distance estimation inaccuracies as well as the inaccurate position information of the reference nodes make it difficult to compute the position (Zheng and Jamalipour, 2009). When considering n reference points and also the error of the distance estimations which makes d_i = ∂-ε. Where, ε is normally considered to be an independent normal random variable with zero mean. This system can be linearized, by subtracting the last equation, into AX≈b. This linear system can be easily solved using standard methods like the least squares approach. If the inverse of $A^T A$ exists, the position of unknown nodes can be expressed as $\hat{x} = (A^T A)^{-1} A^T B$.

If there is an exact linear relationship among the independent, the matrix $A^T A$ will not be invertible. In most applications, there is a near linear relationship among the variables. In this case, the matrix $A^T A$ has an inverse but is ill-conditioned so that a given computer algorithm may or may not be able to compute an approximate inverse and if it does so the resulting computed inverse may be highly sensitive to slight variations in the data (due to magnified effects of rounding error) and so may be very inaccurate. In geometry, the localization unit constituted tetrahedral mesh completely coplanar perfect multicollinearity and nearly coplanar perfect nearly multicollinearity. Overcoming localization unit coplanar or nearly coplanar has great significance for improving the localization accuracy. The study got a series of positioning units from the beacon nodes collected by unknown node, based on their IDs using a method of combination number and then measured the multicollinearity of four beacon nodes in three-dimensional space using a radius ratio method. A threshold Ther was defined as followings:

$$\text{Thre}=\begin{cases}0 & |A^TA|=0\\\rho & |A^TA|\neq 0\end{cases} \tag{13}$$

When, beacon node groups were completely coplanar, the radius ratio was zero; when bacon node groups were not coplanar, a radius ratio value was set to eliminate the group with poor-quality positioning units and reserve good-quality groups. Next, a least square method was made to get corresponding estimated positions using selected beacon node groups and then recorded corresponding radius ratios. A weight was got from a series of radius ratios got from each unknown node. It can be supposed that the bigger the radius ratio is, the better the quality of positioning unit is and thus the bigger its contribution to final positioning result's accuracy is. The expression of weight is as follows:

$$W_i=\text{Thre}_i\Big/\sum_i \text{Thre}_i \tag{14}$$

Finally, multiplied each weight got by corresponding estimated position got and sum corresponding products up to get the final estimated position.

ALGORITHM PERFORMANCE SIMULATION AND ANALYSIS

Localization accuracy, consumption, applicable environment and scale, beacon node proportion, network topology structure adaptability, self-adaptation and fault tolerance are common technical standards for assessing a localization algorithm (Mao and Fidan, 2009). SN3DLE-RSSI algorithm mainly aims at the influence on localization accuracy in two stages of localization process, so localization accuracy is the focus of analysis and evaluation. Moreover, the algorithm involves selection to beacon node groups for which reason some nodes may be not positionable and the coverage of algorithm is also an assessment direction in the study. The study used two specific performance parameter indices Average Localization Error (ALE) and Non-Locatable Node

Ratio (NLNR) to measure algorithm's accuracy and coverage. The two performance indexes are respectively defined as:

Average localization error (ALE): ALE is the ratio between the mean error and communication radius of Euclidean distance from the estimated location of unknown nodes to their true location. Average localization error can be used to evaluate the stability and accuracy of localization algorithm. When the communication radius is given, lower average localization error means higher localization precision and vise versa. The formula is shown as follows:

$$ALE = \frac{\sum_{i=1}^{n}\sqrt{(\hat{x}_i - x_i)^2 + (\hat{y}_i - y_i)^2 + (\hat{z}_i - z_i)^2}}{n \times R} \tag{15}$$

where, n is the number of unknown nodes, (x_i, y_i, z_i) is the unknown node actual position, $(\bar{x}_i, \bar{y}_i, \bar{z}_i)$ is unknown node evaluated position and R is the radio range of sensor nodes.

Non-locatable node ratio (NLNR): NLNR is the ratio of nodes whose positions can not be estimated to unknown nodes and the positioning ratio reflects algorithm's positioning coverage and robustness. Non-positioning ratio is expressed as:

$$NLNP = \frac{n'}{n} \times 100\% \tag{16}$$

here, n' is the number of non-positionable nodes and n is the number of unknown nodes.

The experiment assumed that nodes randomly and evenly distributed in a three-dimensional region of 120×120×120 m. Hundred nodes were deployed randomly. Node's communication radius was set as 100 m and the proportion of beacon nodes was 10-20%. A threshold Thre of 0-0.7 was set. The outlier's occurrence proportion was 1-10%. In order to assess SN3DLE-RSSI algorithm's performance, the study made three experiments with different parameters to compare SN3DLE-RSSI algorithm with mean value smoothing method and 3-sigma smoothing method, respectively.

Experiment 1: The scenario set the gross error ratio as 1-10% and the radius ratio threshold as 0-0.7; the number of beacon nodes was 17. The ALE and NLNR are shown in Fig. 4-5.

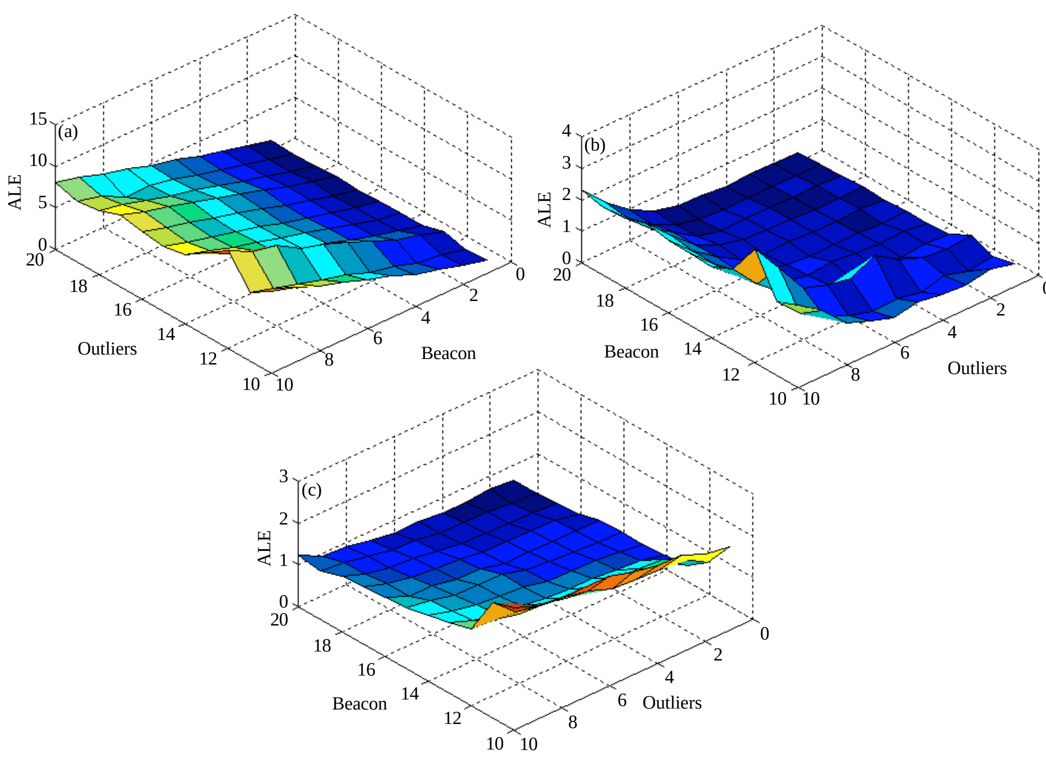

Fig. 4(a-c): Average Localization Error (ALE) of (a) Mean value smoothing, (b) 3-sigma smoothing and (c) SN3DLE-RSSI with different number of beacon nodes and outliers

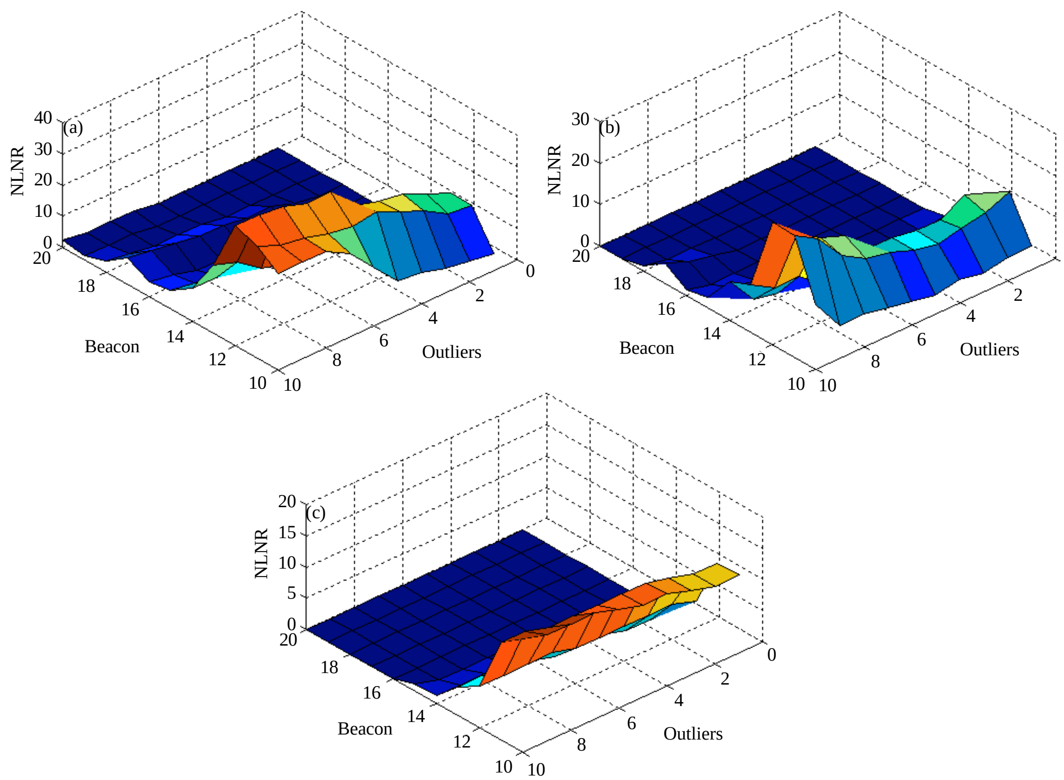

Fig. 5(a-c): Non-locatable node ratio (NLNR) of (a) Mean value smoothing, (b) 3-sigma smoothing and (c) SN3DLE-RSSI with different number of beacon nodes and outliers

In mean value smoothing, the ALE between 11.7268 to 0.9832, the NLNP between 31.1 to 0; in 3-sigma smoothing, the ALE between 3.6139 to 0.35255, the NLNP between 29.2 to 0; the improved algorithm the ALE between 2.9378 to 0.63756, the NLNP between 18.2 to 0.

Experiment 2: The scenario set the gross error ratio as 1-10% and the radius ratio threshold as 0-0.7; the number of beacon nodes was 17. The ALE and NLNR are shown in Fig. 6 and 7.

In mean value smoothing, the ALE between 6.2091 to 0.56928, the NLNP between 27.7 to 0; in 3-sigma smoothing, the ALE between 2.7986 to 0.35255, the NLNP between 12.1 to 0; the improved algorithm the ALE between 1.46502 to 0.69812, the NLNP between 7.2 to 0.

Experiment 3: The scenario set the gross error ratio as 7% and the radius ratio threshold as 0-0.7; the number of beacon nodes was 10-20. The ALE and NLNR are shown in Fig. 8-9.

In mean value smoothing, the ALE between 13.67 to 2.5121, the NLNP between 61.4 to 0; in 3-sigma smoothing, the ALE between 1.7818 to 0.4985, the NLNP between 39.8 to 0; the improved algorithm the ALE between 2.8416 to 0.81752, the NLNP between 36.4 to 0.

Figure 6-9 indicate that neither mean value smoothing method nor 3-sigma smoothing method can remove the influence of outliers on ranging; both ALE and NLNR ratios present irregular variations; SN3DLE-RSSI algorithm's positioning accuracy is better and better as the increase of the number of beacon nodes and the variation curve in the figure is smooth. Moreover, it also can been seen that SN3DLE RSSI algorithm's localization accuracy increases as the increase of threshold Thre but NLNR also increases accordingly and thus reduces node coverage. Therefore, in practical application, threshold Thre can not be set at a high value blindly. As to mean value smoothing method and 3-sigma smoothing method, their localization accuracy and NLNR change disorderly as the increase of threshold Thre. So, SN3DLE-RSSI algorithm can be seen as a method with high adaptability,

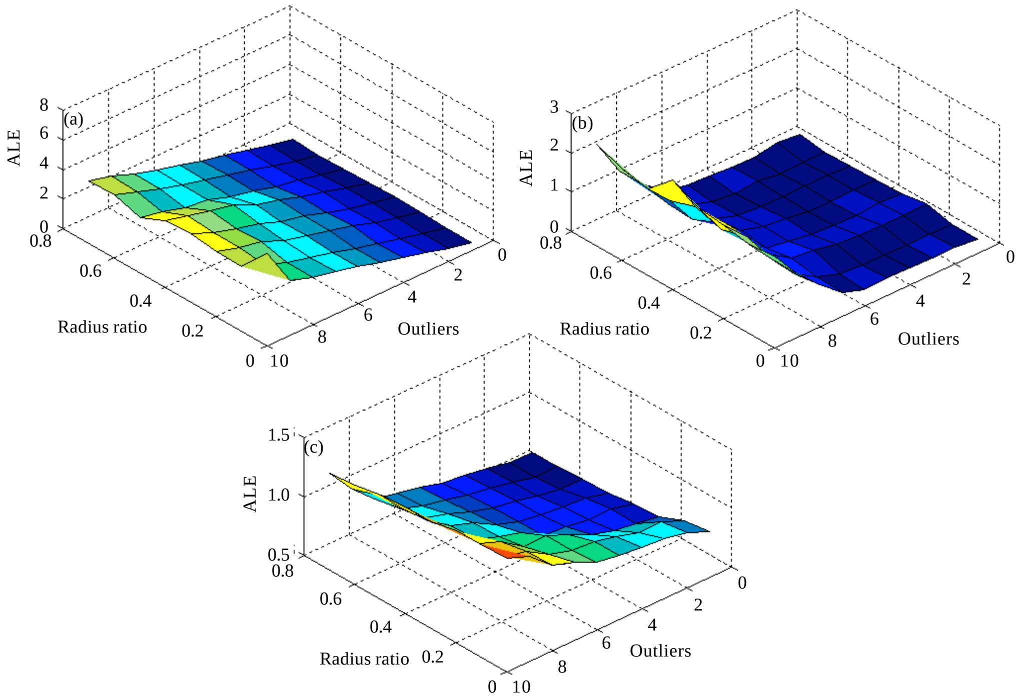

Fig. 6(a-c): Average localization error (ALE) of (a) Mean value smoohing, (b) 3-sigma smoothing and (c) SN3DLE-RSSI with different number of outliers nodes and radius ratio

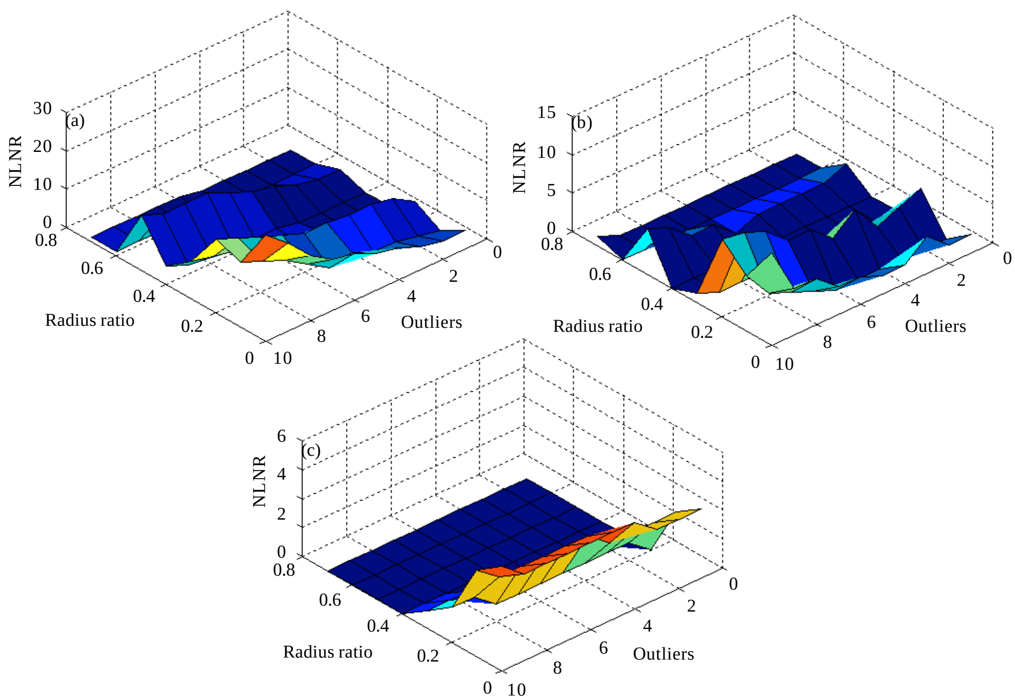

Fig. 7(a-c): Non-locatable node ratio (NLNR) of (a) Mean value smoohing, (b) 3-sigma smoothing and (c) SN3DLE-RSSI with different number of radius ratio and outliers

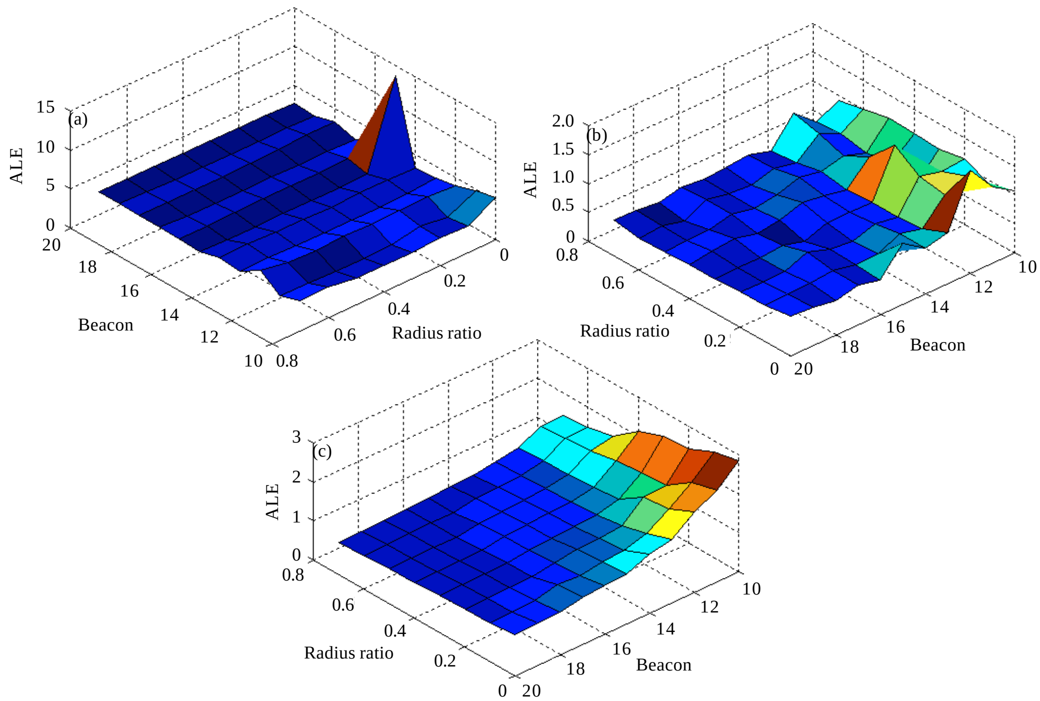

Fig. 8(a-c): Average localization error (ALE) of (a) Mean value smoohing, (b) 3-sigma smoothing and (c) SN3DLE-RSSI with different number of radius ratio and beacon nodes

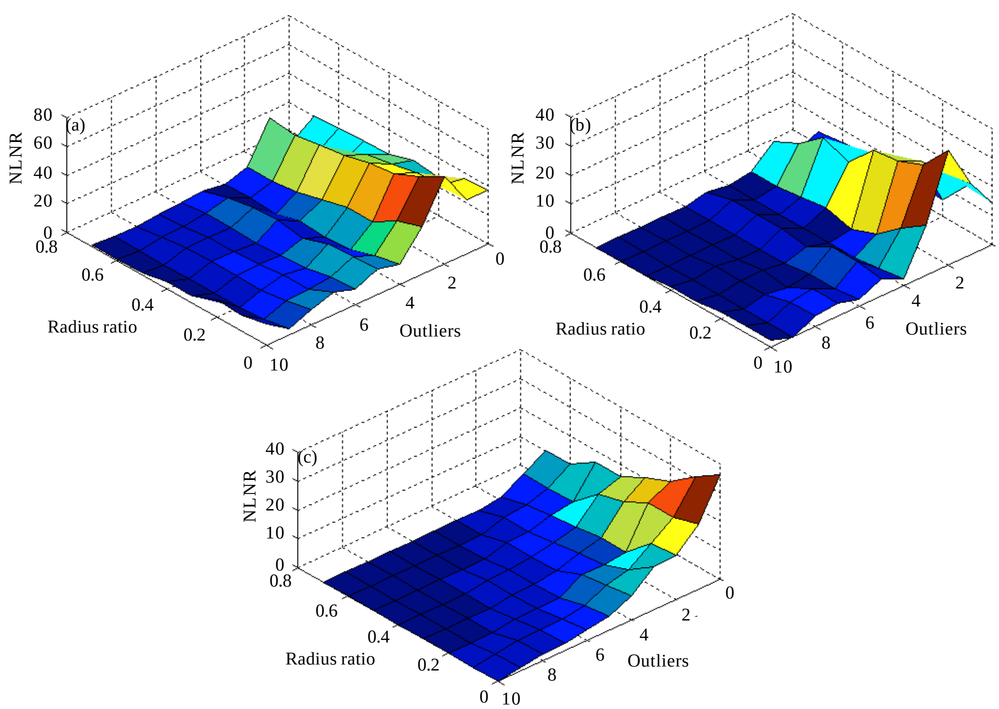

Fig. 9(a-c): Non-locatable node ratio (NLNR) of (a) Mean value smoohing, (b) 3-sigma smoothing and (c) SN3DLE-RSSI with different number of radius ratio and beacon nodes robustness, applicability and localization accuracy which more meets requirements of practical application.

CONCLUSION

Aiming at the practical deployed three-dimensional scenario of sensor nodes, the study adopted proper methods and strategies by analyzing rang errors contained in two stages of positioning and the influence of beacon nodes topology shape on position estimation, to minimize the influence on positioning accuracy. The algorithm idea proposed in the study is applicable to both RSSI-based ranging algorithm and other ranging technology-based positioning algorithms as an optimizing strategy to improve accuracy and stability.

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