Three-dimensional localization algorithm of mobile nodes based on received signal strength indicator-angle of arrival and least-squares support-vector regression

Lieping Zhang1, Huihao Peng1, Jiajie He1, Shenglan Zhang1 and Zuqiong Zhang2

Abstract
Node localization is one of the key technologies in the wireless sensor network research field, which is crucial to the high-accuracy localization of mobile nodes, but the positioning error of traditional algorithms such as received signal strength indicator and angle of arrival is more than 4 m, which has almost no practical value. For example, the localization accuracy of the localization algorithm based on received signal strength indicator will be reduced sharply when affected by signal reflection, multipath propagation, and other interference factors. To solve the problem, a three-dimensional localization algorithm of mobile nodes was proposed in this article based on received signal strength indicator-angle of arrival and least-squares support-vector regression, which fused the ranging information of received signal strength indicator algorithm and the angle of arrival algorithm and optimized the estimated distance of unknown nodes. Next, the mobile node model and least-squares support-vector regression modeling mechanism were built according to the hop count of the shortest distance between nodes. Finally, the unknown mobile nodes were localized based on least-squares support-vector regression modeling. The experimental results showed that compared with the localization algorithms without optimized ranging information or least-squares support-vector regression modeling, the algorithm proposed in this study exhibited significantly improved stability, a reduced mean localization error by more than 50%, and increased localization accuracy.

Keywords
Wireless sensor network, received signal strength indicator, angle of arrival, least-squares support-vector regression, 3D localization

Date received: 2 September 2021; accepted: 31 May 2022
Handling Editor: Lyudmila Mihaylova

Introduction
Moving target localization is one of the hotspots in the wireless sensor network (WSN) research field, which has been widely applied in urban management, environmental monitoring, emergency rescue and disaster relief, military affairs and national defense, and other fields.1 WSN node localization aims to acquire the

1College of Mechanical and Control Engineering, Guilin University of Technology, Guilin, China
2Network and Information Center, Guilin University of Technology, Guilin, China

Corresponding author:
Shenglan Zhang, College of Mechanical and Control Engineering, Guilin University of Technology, Guilin 541006, China.
Email: zsl@glut.edu.cn
target location information mainly by information perception, interaction, and processing between nodes, which can be divided into two types according to different modes of localization, namely, ranging-based algorithms and non-ranging-based algorithms. The ranging-based localization algorithms are often selected in practical application since their accuracy is higher than that of the non-ranging-based localization algorithms. The traditional ranging-based localization algorithms mainly consist of the time of arrival (TOA) measurement, time difference of arrival (TDOA) measurement, and angle of arrival (AOA) measurement. However, the traditional ranging-based localization algorithms are vulnerable to the influences of environmental noise, multipath reflection, and other uncertainties, which can reduce the ranging accuracy, thus affecting the target localization accuracy. As a result, how to improve the traditional ranging algorithm to increase the ranging accuracy is a key problem to be addressed in practical application.

To effectively improve the localization accuracy of ranging-based algorithms, many researchers in related fields have studied the fusion of ranging-based localization algorithms. For example, C Wang and R Yao proposed a localization algorithm fusing AOA and RSSI of directional antennas to solve the low localization accuracy of multi-base stations. An unbalanced fusion of the two measurements, known as 1AOA/nRSSI, was proposed by AT Le et al. to simplify the WSN. Besides, J Wang completed the fusion localization by combining the Kalman filter with the AOA of direct path and RSSI information. The fusion of differential received signal strength indicator (DRSSI) and AOA for recursive localization of a radio frequency (RF) source with unknown transmitted power in none-line-of-sight (NLOS) condition was proposed by Dehghan et al. Although the fusion ranging algorithm can effectively improve the ranging-based localization accuracy, it fails to solve the problems of low anti-noise capability and poor stability during localization.

Consequently, based on the ranging algorithm, different models can be used to localize the targets, such as the circumference-based localization model, hyperbolic localization model, and least-squares support-vector regression (LSSVR). Among them, LSSVR can convert the complicated convex quadratic programming problem into a problem of solving linear equations, which greatly shortens the calculation process, improves the calculation efficiency, and possesses good anti-noise capability. Therefore, the localization accuracy and anti-noise capability of the system can be improved effectively by introducing LSSVR into WSN node localization, and the fusion of LSSVR with WSN localization has been researched by researchers in related fields. For example, Y Zhong et al. put forward the LSSVR localization algorithm based on Gaussian filter RSSI to solve the large errors of RSSI ranging-based localization. M Xia et al. analyzed the ranging principles and factors affecting localization error and proposed the LSSVR location algorithm based on Gaussian filter RSSI.

Z Wang and X Zheng proposed an LSSVR localization algorithm for multi-hop WSNs. Moreover, a modern and high-efficiency algorithm based on a new optimization technique for localization processes in an outdoor environment was presented by Gumaida and Luo in the literature. Despite the wide application of LSSVR in node localization, it mainly supplements or improves a certain method, and there are a few studies on the improvement of RSSI ranging accuracy, rapid LSSVR modeling, and dynamic node prediction. Hence, the advantages of applying the improved ranging-based localization algorithm and the LSSVR to node localization were fully studied in this article. The main contributions of this study are shown as follows:

1. First, the final localization can be realized by fusing multiple methods, so as to improve the localization accuracy of the ranging algorithm. In view of the disadvantages of the traditional RSSI ranging algorithm in practical application, a localization algorithm based on RSSI-AOA was proposed in this study by fusing the ranging information of the RSSI and AOA algorithms, which improved the large ranging error of the RSSI algorithm due to external interference.

2. Second, the motion model of mobile nodes was built in this study using the hop count of the shortest distance between the anchor node and the unknown node. In addition, based on the mapping relationship between the original space and changing space of LSSVR, as well as the modeling principle of mobile nodes, the LSSVR mobile node modeling mechanism was established, so as to improve the anti-noise performance and generalization capability of the algorithm. Furthermore, the nodes involved in LSSVR modeling and responsible for data measurement were set as the modeling nodes.

3. Finally, in this article, LSSVR was used to train the sample set in order to give full play to its high calculation efficiency and good anti-noise performance. In addition to the fusion of the ranging information of RSSI and AOA, the LSSVR mobile node modeling mechanism was employed to predict and estimate the coordinates of the unknown mobile nodes, thereby improving the localization accuracy of unknown nodes, which was verified by means of simulation experiments.
This article was developed as follows. The fusion ranging algorithm based on RSSI and AOA was introduced in section "Fusion ranging algorithm based on RSSI and AOA." The modeling and localization algorithm of mobile nodes based on LSSVR were discussed in section "Fusion ranging algorithm based on RSSI and AOA." The simulation experiments were introduced and the results were analyzed in section "Simulation experiments and result analysis." The conclusion and future prospects were described in section "Conclusion."

Fusion ranging algorithm based on RSSI and AOA

**RSSI ranging algorithm**

The distance between the transmitter and the receiver is calculated by the RSSI ranging algorithm by virtue of the signal strength, transmission energy, and path loss during communication. When the power of transmit signals at the transmitting end is known, the distance between the transmitting end and the receiving end can be estimated by calculating the path loss via the power of signals received at the anchor nodes, and then the locations of unknown nodes can be estimated. According to the definition of RSSI, \( P \) could be determined by RSSI through the received signal strength, which is shown in formula (1) after simplification

\[
P = 10^{\frac{\text{RSSI}}{10}}
\]  

(1)

The RSSI ranging model could be obtained by substituting formula (1) into the logarithmic distance loss model, as shown in formula (2)

\[
\text{RSSI}(d) = \text{RSSI}(d_0) - 10\beta \log\left(\frac{d}{d_0}\right) + n_o
\]  

(2)

wherein, RSSI(\(d\)) indicates the RSSI value received by the receiving node when the transmitting distance is \(d\) (unit: dBm). RSSI(\(d_0\)) means the power reference value of signals received by the receiving nodes when the transmitting distance is \(d_0\). \(\beta\) stands for the path loss index, \(n_o\). Since the RSSI ranging accuracy may be reduced by the inherent characteristics of nodes and such uncertainties as the air humidity, atmospheric pressure, and temperature in outdoor environments, the fusion of the RSSI algorithm was fused with other ranging algorithms in this study, so as to improve the ranging accuracy of the algorithm.

**AOA ranging algorithm**

In the AOA ranging algorithm, the ranging must be performed by the ultrasonic sensor or array antenna mounted on the nodes. The obtained angle relationship between the anchor node and the unknown node is subjected to geometric calculation, and then the location of the unknown node can be estimated. The ranging principle of the AOA algorithm is shown in Figure 1.

In Figure 1, the location coordinates of the fixed nodes \(O_1\) and \(O_2\) are \((x_1, y_1)\) and \((x_2, y_2)\), respectively. Assuming that the location coordinate of the unknown node \(M\) is \((x, y)\), the angles between the directions from the fixed nodes \(O_1\) and \(O_2\) to the unknown node \(M\) and the horizontal direction, namely, the angles of incidence, are \(\theta_1\) and \(\theta_2\), respectively, according to the measurement of the array antenna. The equation can be listed as shown in formula (3)

\[
\begin{align*}
\tan \theta_1 &= \frac{y-y_1}{x-x_1} \\
\tan \theta_2 &= \frac{y-y_2}{x-x_2}
\end{align*}
\]  

(3)

The location coordinate of the unknown node \(M\) can be obtained by solving formula (3) simultaneously (formula (4))

\[
\begin{align*}
x &= \frac{(y_2-y_1 \tan \theta_2) - (y_1-y_2 \tan \theta_1)}{\tan \theta_1 - \tan \theta_2} \\
y &= \frac{(x_2-y_2 \cot \theta_1) - (x_1-y_2 \cot \theta_2)}{\cot \theta_2 - \cot \theta_1}
\end{align*}
\]  

(4)

In the AOA ranging algorithm, only the angles of incidence from two or more unknown nodes to the fixed node are required to complete the localization of the unknown nodes, so the hardware cost needed for this algorithm in ranging process is relatively low. Nevertheless, the localization accuracy of the AOA algorithm decreases with the increase in the distance between the base station and the terminal, and the localization accuracy is low when it is not improved, so this algorithm is generally not used alone.

**RSSI-AOA ranging algorithm**

In actual localization process, signal reflection, multipath propagation, and other factors can increase the
error of RSSI ranging, but the introduction of angle information (AOA) is capable of reducing the influence of these factors on RSSI ranging. Accordingly, the ranging algorithm fusing RSSI and AOA can improve the localization accuracy of unknown nodes prominently, which is of certain study significance.

The localization principle based on the ranging algorithm is shown in Figure 2, where one unknown target node and four anchor nodes are arranged in the localization area. Figure 2(a) presents the RSSI ranging-based localization principle. Circles were drawn with each anchor node as the center and the communication distance $d_i$ as the radius, and the overlapping part of the four circles was the estimated area where the unknown target node was located. Figure 2(b) shows the AOA ranging-based localization principle. The line linking each anchor node and the unknown node formed an angle of $\phi_i$ with the horizontal line, and the shadow area formed by the intersection of the four lines was regarded as the estimated area of the unknown node. Figure 2(c) displays the localization principle based on RSSI-AOA fusion ranging. The localization algorithm integrated the results of two measurements, and if the estimated shadow area was reduced significantly, the localization accuracy of unknown node could be further improved.

First, the RSSI model was replaced with the logarithmic distance path loss model in the path loss model (formula (5))

$$L_{ij} = 10 \lg \left( \frac{P_T}{P_{ij}} \right) (dB) \quad (5)$$

wherein, $L_{ij}$ and $P_{ij}$ indicate the path loss and receiving power of the sensors $i$ and $j$ in communication, respectively, and $P_T$ is the reference energy.

Therefore, $L_{ij}^A$ and $L_{ij}^B$ can be calculated as per formula (6)

$$\begin{align*}
L_{ij}^A &= L_0 + 10 \beta \lg \frac{|x_i - x_j|}{d_{ij}} + n_{ij} \quad (i,j) \in A \\
L_{ij}^B &= L_0 + 10 \beta \lg \frac{|x_i - x_j|}{d_{ik}} + n_{ik} \quad (i,k) \in B
\end{align*} \quad (6)$$

wherein, $L_0$ indicates the path loss when the reference distance between nodes is $d_0$, $\beta$ refers to the path loss coefficient, and $n_{ij} \sim (0, \sigma^2_{ij})$ and $n_{ik} \sim (0, \sigma^2_{ik})$ are the shielding factors. $A = \{(i,j)||x_i - a_j|| \leq R, i = 1, \ldots, M, j = 1, \ldots, N\}$ is the connection between the anchor nodes and the target nodes, $B = \{(i,k)||x_i - x_k|| \leq R, i, k = 1, \ldots, M, i \neq k\}$ is the connection between the target nodes and the target nodes, where $R$ is the communication range of the sensor node.

The maximum likelihood estimate of distance between every two nodes can be obtained from the RSSI model, as shown in formula (7)

$$\begin{align*}
\hat{d}_{ij}^A &= d_i 10^{\frac{L_{ij}^A - L_0}{10\beta}}, (i,j) \in A \\
\hat{d}_{ik}^B &= d_k 10^{\frac{L_{ij}^B - L_0}{10\beta}}, (i,k) \in B
\end{align*} \quad (7)$$

In addition, receiving antennas should be placed in the anchor nodes to obtain the azimuth angle and elevation angle measured by AOA (Figure 3).

According to the geometrical relationship in Figure 3, the relationship shown in formula (8) could be obtained by measuring and modeling the angle information

$$\begin{align*}
\phi_{jk}^A &= \arctan \frac{x_j - a_j}{y_j - a_j} + \gamma_{ij} \quad (i,j) \in A \\
\phi_{jk}^B &= \arctan \frac{x_k - x_j}{y_k - y_j} + \gamma_{ik} \quad (i,k) \in B \\
\alpha_{ij}^A &= \arccos \frac{\|x_i - x_j\|}{|y_i - y_j|} + \nu_{ij} \quad (i,j) \in A \\
\alpha_{jk}^B &= \arccos \frac{\|x_j - x_k\|}{|y_j - y_k|} + \nu_{ik} \quad (i,k) \in B
\end{align*} \quad (8)$$

wherein, $x_i = [x_{i1}, x_{i2}, x_{i3}]^T$ indicates the coordinate of the target node. $\alpha_i = [\alpha_{i1}, \alpha_{i2}, \alpha_{i3}]^T$ represents
coordinate of the anchor node. \( d_{ij}, \phi_{ij}, \) and \( \alpha_{ij} \) stand for the distance, azimuth angle, and elevation angle between the \( i \)th target node and the \( j \)th anchor node, respectively.

With a given observation vector

\[
\theta = \begin{bmatrix} L^T \\ \phi^T \\ \alpha^T \end{bmatrix}, \quad (\theta \in \mathbb{R}^{3(|A| + |B|)})
\]

where

\[
L = \begin{bmatrix} L^A \\ L^B \end{bmatrix}, \quad \phi = \begin{bmatrix} \phi^A \\ \phi^B \end{bmatrix}, \quad \text{and} \quad \alpha = \begin{bmatrix} \alpha^A \\ \alpha^B \end{bmatrix}
\]

Formula (9) is a function of the PDF (Probability Density Function) model, and formula (9) can be used to deduce the relationship shown in formula (10)

\[
p(\theta | x) = \prod_{i=1}^{3(|A| + |B|)} \frac{1}{2\pi\sigma^2} \exp \left\{ -\frac{(\theta_i - f_i(x))^2}{2\sigma^2} \right\} \quad (9)
\]

\[
f(x) = \begin{bmatrix} \cdot \\ \cdot \\ \cdot \end{bmatrix}, \quad \sigma = \begin{bmatrix} \cdot \\ \cdot \\ \cdot \end{bmatrix}
\]

The maximum likelihood estimate method was finally adopted. The distance information of multiple neighbor nodes can be used to minimize the difference between the measured distance and the estimated distance in node localization. In the RSSI-AOA ranging algorithm, the maximum likelihood estimate method could be used to calculate the coordinates of target nodes, as shown in formula (11)

\[
\hat{x} = \arg\min_x \sum_{i=1}^{3(|A| + |B|)} \frac{1}{\sigma_i^2} (\theta_i - f_i(x))^2 \quad (11)
\]

**Modeling and localization algorithm of mobile nodes based on LSSVR**

**Localizaiton of mobile nodes based on LSSVR**

**Modeling of mobile nodes.** In this study, the selected mobile node model was static for anchor nodes and mobile for unknown nodes. During node modeling, the mapping relation among the unknown mobile nodes in the three-dimensional (3D) space is shown in Figure 4. In the input space \( \mathbb{R}^n \), the distance vector \( V \) corresponded to the node \( M \) one to one, forming the mapping surface \( Z \). Therefore, there was a clear corresponding relationship between the distance vector from the anchor node to the unknown node and the coordinate of unknown node, that is, the calculation process of unknown node localization can be converted to the mapping process from the distance vector to the coordinates, thus modeling the mobile nodes.

It was assumed that \( M \) sensor nodes \( \{S_1, S_2, \ldots, S_M\} \) with the same wireless range \( R \) were randomly placed in the 3D space detection area \( Q = [0, D] \times [0, D] \times [0, D] \),

\[
\text{Figure 4. The mapping relation among the unknown mobile nodes in the three-dimensional (3D) space.}
\]
and that there are $L$ anchor nodes $\{S_1, S_2, \ldots, S_L\}$. Assuming that the hop count of the shortest distance from the node $S_i$ to the anchor node $S_j$ is $h = (S_i, S_j)$, the minimum hop count from the node to each anchor node could form the hop count vector (formula (12))

$$R_i = [h(S_i, S_1), h(S_i, S_2), \ldots, h(S_i, S_L)]$$ (12)

Assuming that the coordinate of the unknown node $i$ is $T_{i-1}(x_{i-1}, y_{i-1}, z_{i-1})$ at the time of $t_{i-1}$, the neighboring nodes were localized at an interval of $\Delta t$. If the unknown node moved in a random direction at a speed $v$, the mobile model of the unknown node is shown in formula (13)

$$f(V) = f((x_i, y_i, z_i)|(x_{i-1}, y_{i-1}, z_{i-1})) = \frac{1}{\pi(v \times \Delta t)^2}$$ (13)

**LSSVR modeling principle.** LSSVR, based on the statistical learning theory, transforms the training samples in low-dimensional spaces into feature vectors in high-dimensional spaces, then constructs a segmentation hyperplane in high-dimensional spaces, and finally fits the samples with the least square error. The principle of the LSSVR learning machine is shown in Figure 5.

In Figure 5, $x \in R$ as a one-dimensional input space, $(x_i, y_i)$ is a training sample composed of input vector $x_i$ and output vector $y_i$, and $\phi : x \rightarrow x^\phi$ is the mapping rule from the input space to the high-dimensional space. $(x^\phi_i, y_i)$ is a training sample composed of feature vector $x^\phi_i$ and output value $y_i$. $y = w \cdot x^\phi + b$ is the hyperplane of the optimal segmentation of the high-dimensional space of regression fitting, $y = w \cdot \phi(x) + b$ is the corresponding optimal regression curve, and $w$ and $b$ are the parameters of the split hyperplane. During WSN node localization, the regression model was established by mapping the node measurement information, thereby obtaining the location estimation of target nodes.

It was assumed that $M$ sensor nodes $\{S_1, S_2, \ldots, S_M\}$ with the same wireless range were randomly placed in the plane detection area $Q = [0, D] \times [0, D]$, and there were $L$ anchor nodes and $M-L$ unknown nodes. The locations of the virtual nodes were sampled in the detection area, and the training samples were acquired. Later, the LSSVR learning machine was used to learn the training samples, and the localization models X-LSSVR and Y-LSSVR based on LSSVR were obtained. The specific LSSVR modeling steps are as follows.

With the training sample set assumed as $X = \{(v_i, y_i)|v_i \in R^n, y_i \in R, i = 1, 2, \ldots, m\}$, the LSSVR learning machine was employed to solve the optimal problem shown in formula (14)

$$\min_{w, b, \xi} = \frac{1}{2}||w||^2 + \frac{1}{2} \gamma \sum_{i=1}^{m} \xi _i^2$$ (14)

wherein, $\xi _i$ indicates the fitting error of the regression segmentation hyperplane, $\gamma$ ($\gamma > 0$) means the regularization parameter. $b$ represents the deviation. $w$ stands for the weight vector, and $\xi$ indicates the random error.

Since the solution of the optimal problems shown in formula (14) was complicated, the Lagrange multiplier method was applied to simplify the solution steps greatly. The optimal problems were transformed into dual problems by introducing the non-negative coefficient $\alpha_i$ as the weight of constraint conditions (formula (15)). The derivative of formula (15) was calculated and transformed into the matrix form, as shown in formula (16)

$$L(w, b, \xi, \alpha) = J(w, \xi) - \sum_{i=1}^{m} \alpha_i \{w \cdot \phi(v_i) + b + \xi_i - y_i\}$$ (15)
Localization of mobile nodes based on LSSVR. Assuming that there were nodes \( S_1, S_2, \) and \( S_3 \) randomly distributed in the 3D space detection area \( Q = [0, D] \times [0, D] \times [0, D] \), circles were drawn separately with \( S_1, S_2, \) and \( S_3 \) as the center and the wireless range \( R \) as the radius, as shown in Figure 6. The data in the shadow area of intersection were used to build the LSSVR model. The nodes involved in the LSSVR modeling and responsible for data measurement were regarded as the modeling nodes. \( T_i \) indicates the location of the target at the time of \( t_i \).

At the time of \( t_1, t_2, \) and \( t_3 \), the nodes \( T_1, T_2, \) and \( T_3 \) were all located in the area A (Figure 6), so the nodes for measurement were always \( S_1, S_2, \) and \( S_3 \). If \( f_1(V) \) was obtained after localization based on the nodes \( S_1, S_2, \) and \( S_3 \) at the time of \( t_1 \), \( f_1(V) \) could be used directly to calculate the coordinates of target nodes at the time of \( t_1, t_2, \) and \( t_3 \). At the time of \( t_4 \) and \( t_5 \), the target nodes \( T_4 \) and \( T_5 \) located in the areas B and C, respectively, and the nodes for measurement still contained the modeling nodes \( S_1, S_2, \) and \( S_3 \). In consequence, the vector formed by the hop count of the shortest distance of nodes \( S_1, S_2, \) and \( S_3 \) at the time of \( t_4 \) and \( t_5 \) is shown in formula (19)

\[
R_i = [h(S_1, S_i), h(S_2, S_i), \ldots, h(S_L, S_i)]
\]  

(19)

The location of the target nodes could be calculated by inputting \( R_i \) into \( f_1(V) \).

After the introduction of LSSVR, the problem of complex convex quadratic programming is transformed into the problem of solving linear equations, which greatly reduces the calculation amount of the algorithm and improves the calculation efficiency.

3D localization algorithm of mobile nodes based on RSSI-AOA and LSSVR

The 3D localization algorithm of mobile nodes based on RSSI-AOA and LSSVR proposed in this study was carried out as per the following steps:

Step 1: \( M \) sensor nodes \( \{S_1, S_2, \ldots, S_M\} \) with the same wireless range were randomly arranged in the 3D space detection area \( Q = [0, D] \times [0, D] \times [0, D] \). Each node was provided with a storage module to store the hop count of the shortest distance and other information of each node, and there were \( L \) anchor nodes \( \{S_1, S_2, \ldots, S_L\} \). Assuming that the coordinate of the unknown node \( S_i \) was \((x_i, y_i, z_i)\), the hop count of the shortest distance from the node \( S_i \) to the node \( S_j \) was \( h(S_i, S_j) \).

Step 2: the information was propagated among the neighbor nodes, so each node could obtain the hop count of the shortest distance of each anchor node.
Then, at an interval of $\Delta t$, the hop count vector $R_i = [h(S_i, S_1), h(S_i, S_2), \ldots, h(S_i, S_v)]$, the location coordinates of anchor nodes, and the distance and angle information from the unknown node were sent by the anchor node to the rendezvous node.

Step 3: when the rendezvous node received the data from each anchor node, the RSSI-AOA localization algorithm was used to calculate the results $\hat{x}^i, \hat{y}^i, \hat{z}^i$, and the hop count vector $R_i$ obtained from the measurement of the anchor node was taken as the sample set $(U_i, U_j, U_z)$

$$
\begin{align*}
U_i &= \{(R_i, x_i)|i = 1, 2, \ldots, L\} \\
U_j &= \{(R_j, y_j)|j = 1, 2, \ldots, L\} \\
U_z &= \{(R_z, z_i)|i = 1, 2, \ldots, L\}
\end{align*}
$$

(20)

Step 4: LSSVR was used to train the sample set mentioned above, and the optimal problems shown in formula (21) were solved in combination with the radial basis function

$$
\min_{w, b, \xi} (w, b, \xi) = \frac{1}{2} \|w\|^2 + \frac{1}{2} \sum_{i=1}^m \xi_i^2
$$

(21)

wherein, $w$ indicates the weight vector. $\xi$ refers to the random error. $b$ is the deviation. $\gamma(\gamma>0)$ indicates the regularization parameter, and $\xi_i$ represents the fitting error of the regression segmentation hyperplane.

Step 5: the parameters obtained from Step 4 were substituted into the radial basis function, as shown in formula (22)

$$
K(R_m, R_n) = \exp\left(-\frac{(R_m - R_n)^2}{2\sigma^2}\right)(m, n = 1, 2, \ldots, L)
$$

(22)

Step 6: the kernel function parameters and regularization parameter obtained from Step 5 were used to obtain the Lagrange multiplier, thus simplifying the problem, as shown in formula (23)

$$
\begin{bmatrix}
0 \\
e^T \\
\Omega + \gamma^{-1}I
\end{bmatrix}
\begin{bmatrix}
b \\
a
\end{bmatrix} =
\begin{bmatrix}
0 \\
y
\end{bmatrix}
$$

(23)

Step 7: the decision function was obtained. The localization model finally obtained is shown in formula (24)

$$
\hat{x} = f_x(R) = \sum_{i=1}^L a_iK(R_i, R_i) + b
$$

(24)

Algorithm 1. The flow chart of RSSI-AOA-LSSVR algorithm.

1. Input: initializing the input parameters: anchor nodes $\{S_1, S_2, \ldots, S_v\}$
2. for $i = 1$: virtualnode _num
3. $R_i = [h(S_i, S_1), h(S_i, S_2), \ldots, h(S_i, S_v)]$
4. Use the RSSI-AOA localization algorithm to calculate the results $\hat{x}^i, \hat{y}^i, \hat{z}^i$
5. Get the training sample set: $(U_i, U_j, U_z)$
6. LSSVR training positioning model:
7. Select the radial basis function using equation (21)
8. Get the trained positioning model $X$-LSSVR
9. Calculate $\hat{x}$ using equation (24)
10. Similarly, obtain $\hat{y}, \hat{z}$
11. Output: estimating locations $(\hat{x}, \hat{y}, \hat{z})$
12. End

And $\hat{y}, \hat{z}$ could be obtained accordingly, then the estimated coordinate of the unknown node was $(\hat{x}, \hat{y}, \hat{z})$. The fusion algorithm is expressed as follows. The flow chart of the fusion algorithm is shown in Figure 7.

Simulation experiments and result analysis

To evaluate the superiority and effectiveness of the algorithm proposed in this study, simulation experiments were carried out in Matrix Laboratory (MATLAB)-R2017b for verification. Assuming that the target mobile nodes moved at a constant speed in the $100 \times 100 \times 100$ m 3D scene, 200 sensor nodes were randomly placed in the area, 40 of which were randomly selected as the anchor nodes, and the remaining 160 served as the unknown nodes. The setting of experiment parameters is shown in Table 1, and the moving track of the unknown nodes in the 3D space for one moment is manifested in Figure 8. In the MATLAB simulation experiments, the RSSI, AOA, RSSI-AOA, RSSI-LSSVR, and AOA-LSSVR algorithms were compared with the 3D localization algorithm of mobile nodes based on RSSI-AOA and LSSVR, and the influences of the connectivity of the anchor node as well as the mobility of the unknown nodes on the localization error were analyzed.

Influence of anchor node density on localization error

The anchor node density is one of the important indexes of WSN localization, which is inversely proportional to the mean localization error and directly proportional to the hardware cost and system power consumption. As a result, it is of great importance to select the appropriate anchor node density for the control over the localization accuracy and hardware cost in practical application. The influence of the anchor node density on the mean localization error of the system is shown in Figure 9. It
was revealed that the localization error of the AOA-LSSVR algorithm was large and the most unstable, with a fluctuation range of 0.5–4 m. The localization errors of the remaining five algorithms were relatively small and stable, and the RSSI-AOA-LSSVR localization algorithm had the smallest mean localization error, with a fluctuation range of 0.24–0.38 m, indicating that the algorithm proposed in this article can ensure high localization accuracy in the case of small anchor node density. In practical application, the anchor node density can be adjusted to reduce the hardware cost and power consumption of the system.

Figure 7. The flow chart of RSSI-AOA-LSSVR algorithm.

Table 1. The setting of experiment parameters.

| Experiment parameters   | Numerical value |
|-------------------------|-----------------|
| Step length (t)         | 10 m            |
| Carrier frequency       | 2.4 GHz         |
| Range (R)               | 40 m            |
| Path loss index (β)     | 2               |
| Emission speed (c)      | Light speed     |
| Moving speed (v)        | 1 m/s           |

Figure 8. The moving track of the unknown nodes in the 3D space.
In WSN localization, the connectivity of anchor nodes had a direct influence on the mean localization error of the system, which is generally inversely proportional to the localization error of the system. In MATLAB simulation experiments, the density of anchor nodes was first set as 20%, and the variation range of the wireless range was 25–60 m. According to the simulation results of the connectivity and localization error (Figure 10), the AOA-LSSVR localization algorithm presented the largest variation and localization error (error range = 0.47–4.65 m). The mean localization errors of the remaining five algorithms were small when the wireless range of the anchor nodes was small, and the variation of the curve decreased gradually with the gradual increase in the wireless range. Among the algorithms, the curve of the RSSI-AOA-LSSVR localization algorithm was the flattest, indicating that this algorithm is basically not influenced by the connectivity. Moreover, its mean localization error was kept at about 0.17 m, which was reduced by 50%–96%, showing high localization accuracy and strong stability.

**Influence of mobility of unknown nodes on localization error**

The mobility of unknown nodes is an uncontrollable factor during actual localization, which has a certain influence on the localization accuracy. The simulation results of the mobility and mean localization error of unknown nodes are shown in Figure 11. It was manifested that the localization error of each algorithm increased as the moving speed of unknown nodes was increased. The localization error ranges of the AOA localization algorithm, RSSI localization algorithm, and RSSI-AOA localization algorithm were 3.6–7.4 m, 4.8–5.5 m, and 1.8–2.54 m, respectively, and all the three algorithms presented large error and curve fluctuations. The remaining three localization algorithms showed very stable error curves and relatively small mean localization errors. Specifically, the localization errors of both AOA-LSSVR and RSSI-AOA-LSSVR localization algorithms were within 0.7 m, while the mean localization error of the RSSI-AOA-LSSVR algorithm was maintained at the lowest level, with the...
Mean localization accuracy of about 0.4 m, showing good overall performance.

Mean localization errors of mobile nodes

Figure 12 illustrates the comparison of the mean localization errors among the six algorithms for the localization of the unknown nodes. The AOA-LSSVR, AOA, and RSSI localization algorithms showed great curve fluctuation ranges and localization errors, while the RSSI-AOA, RSSI-LSSVR, and RSSI-AOA-LSSVR localization algorithms exhibited small curve fluctuation ranges and localization errors on the whole. At the same time, the RSSI-AOA-LSSVR localization algorithm had the smallest localization error, which was above 50% smaller than that of the remaining five algorithms, and it had the smallest curve fluctuation range as well, presenting better stability and higher localization accuracy.

Conclusion

In this study, a 3D localization algorithm of mobile nodes based on RSSI-AOA and LSSVR was proposed to cope with the low localization accuracy and poor anti-interference capability of the RSSI localization algorithm in WSN during the localization of mobile nodes, which not only optimized the parameters of LSSVR but also studied the ranging and LSSVR modeling. To reduce the ranging error, the ranging information of the RSSI and AOA algorithms was fused. Moreover, the LSSVR modeling mechanism was established based on the hop count of the shortest distance between nodes, and it was used to predict the locations of the target nodes, so as to improve the anti-noise capability and stability of the system. The following conclusions can be drawn according to the theoretical study and simulation experiments in this article:

1. In this study, the ranging information of the RSSI and AOA algorithms was fused to localize the targets, and the results showed that compared with the RSSI or AOA ranging-based localization algorithm alone, the RSSI-AOA localization algorithm displayed an obviously smaller localization error but still poor stability. Consequently, the LSSVR modeling algorithm was added for predicted localization according to the mapping relationship between the anchor nodes and the unknown nodes. The results of the MATLAB simulation experiments revealed that the localization error fluctuation range of the RSSI-AOA-LSSVR localization algorithm was 0.24–0.38 m under the influence of the anchor node density, showing the best and relatively stable performance on the whole. The localization error curve was the flattest when affected by the connectivity of the anchor nodes, with a mean localization error of 0.17 m, which was reduced by 50%–96% compared with other localization algorithms. In general, the RSSI-AOA-LSSVR localization algorithm had higher localization accuracy, better anti-interference capability, and higher stability.

2. Although the effectiveness of the 3D localization algorithm of mobile nodes based on RSSI-AOA and LSSVR proposed in this study was verified by theoretical analysis and simulation experiments, the localization in this study only targeted at the unknown nodes moving at a constant speed, while the unknown nodes in actual localization are often moving at variable and irregular speed. As a result, how to realize high-accuracy 3D localization of unknown nodes moving irregularly at non-uniform speed is the main content of future study.

Declaration of conflicting interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: This work was supported by the National Natural Science Foundation of China (no. 61741303), the Key Laboratory of Spatial Information and Geomatics (Guilin University of Technology) (no. 19-185-10-08), and the Scientific Research Basic Ability Improvement Project of
Young and Middle-aged Teachers in Colleges and Universities in Guangxi (no. 2021KY0260.

**ORCID iDs**
- Lieping Zhang https://orcid.org/0000-0002-6976-846X
- Huihao Peng https://orcid.org/0000-0002-2731-5278
- Zuqiong Zhang https://orcid.org/0000-0003-3294-8341

**Data availability**
Data sharing is not applicable to this article as no data sets were generated or analyzed during this study.

**References**

1. Zou D, Chen S, Han S, et al. Design of a practical WSN based fingerprint localization system. *Mobile Netw Appl* 2020; 25(2): 806–818.
2. Li W, Yang H, Fan M, et al. A fuzzy adaptive tightly-coupled integration method for mobile target localization using SINS/WSN. *Micromachines* 2016; 7(11): 197.
3. Han S, Gong Z, Meng W, et al. Automatic precision control positioning for wireless sensor network. *IEEE Sens J* 2016; 16(7): 2140–2150.
4. Wu W, Pan Z and Zhang X. Research on positioning technology of WSN based on range-free. *J Guiyang Univ Nat Sci* 2017; 12(2): 35–37.
5. Jeon JH, Lim JM, Yoo SH, et al. Development of 3-dimensional position/attitude determination radio-navigation system with FLAOA and TOA measurements. *J Position Navig Tim* 2018; 7(2): 61–71.
6. Zhang H, Chen D, Peng Q, et al. A revised TDOA wireless sensor network node location algorithm. *Chin J Sensor Actuat* 2015; 28(3): 412–415.
7. Xue W, Li Q, Hua X, et al. A new algorithm for indoor RSSI radio map reconstruction. *IEEE Access* 2018; 6: 76118–76125.
8. Xiong H, Yang R, Liang X, et al. 3D AOA localization using UAVs monocular vision. *Comput Eng Appl* 2020; 56(17): 210–216.
9. Qiu Y, Lv P, Liu X, et al. Research on prefilter location algorithm based on RSSI. *Radio Eng* 2021; 51(5): 367–372.
10. Wang C and Yao R. Fusion algorithm for antenna array AOA and RSSI. *Comput Eng Des* 2018; 39(6): 82–86.
11. Le A, Tran L, Huang X, et al. Unbalanced hybrid AOA/ RSSI localization for simplified wireless sensor networks. *Sensors* 2020; 20(14): 3838.
12. Wang J. Research on fusion localization algorithm based on AOA and RSSI. Chongqing, China: Chongqing University of Posts and Telecommunications, 2018.
13. Dehghan SMM, Moradi H, Shahabadi M, et al. Fusion of DRSSI and AOA for aerial localization of an RF source with unknown transmitted power. *Int J Robot Autom* 2016; 31(3): 156–165.
14. Li X, Tan X and Zhao C. PSO-LSSVR assisted GPS/INS positioning in occlusion region. *Sensors* 2019; 19(23): 5256.
15. Zhang Y, Fan H and Wang Y. WLAN heterogeneous terminal location method based on DBSCAN-GRNN-LSSVR algorithm. *Appl Res Comput* 2019; 36(4): 1174–1177.
16. Zhong Y, Liang R and Huang X. LSSVR wireless sensor network location algorithm based on Gaussian filter RSSI. *Mod Electron Techn* 2017; 40(11): 6–9.
17. Xia M, Zhang X and Zhu Y. Real time localization algorithm based on local linear embedding optimization in sensor networks. *Cluster Comput* 2019; 22(suppl. 2): 4173–4178.
18. Wang Z and Zheng X. Least-squares support vector regression-based localization algorithm in multi-hop wireless sensor networks. *Chin J Sensor Actuat* 2017; 30(11): 1747–1751.
19. Gumaida BF and Luo J. A hybrid particle swarm optimization with a variable neighborhood search for the localization enhancement in wireless sensor networks. *Appl Intell* 2019; 49(10): 3539–3557.
20. Yuan H and Wang P. Weighted centroid midpoint localization algorithm based on RSSI. *Technology Wind* 2021; 14: 76–77.
21. Yue Z and He W. Carrier phase based indoor AOA/ToF localization. *Telecommun Eng* 2021; 61(5): 614–620.
22. Peper F, Leibnitz K, Teramae J, et al. Low-complexity nanosensor networking through spike-encoded signaling. *IEEE Internet Things* 2017; 3(1): 49–58.
23. Zhang Y, Li F and Wang Y. Indoor positioning algorithm for WLAN based on KDDA and SFLA-LSSVR. *J Comput Res Dev* 2017; 54(5): 979–985.