RSSI-based Positioning with Self-Adapting FWA for Software-Defined Wireless Sensor Networks

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***Abstract*—RSSI-based Positioning in software-defined wireless sensor networks faces the dilemma of improving accuracy and reducing power consumption. Based on the construction of centralized positioning scenes, this paper establishes a mathematical model to minimize the positioning error by making full use of the RSSI between blind nodes. On this basis, by designing the blind node positioning matrix, the multi-node positioning is transformed into single-objective optimization, and the self-adapting Fireworks algorithm is used to solve the model. The simulation experiment achieves average positioning error of 1.88m on the open dataset, which is currently optimal.**

***Index Terms*—Positioning, RSSI, FWA, SDWSN.**

I. Introduction

WITH the help of software-defined paradigm, software-defined wireless sensor networks (SDWSN) as the next generation of wireless sensor networks (WSN) came into being [1]. Positioning is an important support of the sensing function, and its performance directly affects the value of sensing information [2]. Therefore, since the birth of WSN, positioning has been a hot topic in academic research.

Since the received signal strength indication (RSSI) is convenient to obtain without deploying additional hardware, RSSI-based positioning has become the preferred choice for a large number of networks [3]. The basic principle of RSSI-based positioning is to convert the transmission loss of wireless signal into communication distance. However, due to the time-varying nature of wireless channels, there is usually a certain error in distance conversion [4]. At the same time, considering the resource-constrained feature of nodes, scholars have made a lot of explorations in balancing the accuracy and power consumption of positioning.

In earlier studies, accuracy preceded power consumption. On the basis of trilateral positioning, increasing the number of anchor nodes from spatial dimension [5] or repeatedly positioning from time dimension [6] could effectively reduce errors, but inevitably increase the communication overhead.

In order to increase energy efficiency, anchor scheduling scheme activates as few anchors as possible while ensuring the positioning accuracy [7]. However, this method is only suitable for the case where the proportion of anchors is high. Authors in [8] designs a positioning platform with limited energy consumption, which integrates range-based and range-free positioning algorithms to improve the accuracy, but does not reduce the error fundamentally.

In summary, the above schemes do not thoroughly solve the contradiction between the accuracy and the power consumption. The root cause is that they only use the RSSI between the anchor node and the blind node, but ignore the RSSI between the blind nodes (bRSSI)! On the one hand, the high cost of anchor nodes leads to limited deployment, so excessive dependence on the anchor node results in difficulty in improving the accuracy. On the other hand, a large number of bRSSI are not fully utilized, and they are usually acquired when the network topology is built [9].

Therefore, in this paper, a mathematical model is built to minimize the positioning error for SDWSN by making full use of bRSSI. Then, considering the complexity of solving the model, swarm intelligence algorithm - fireworks algorithm (FWA) - is adopted. Referring to the proximity similarity, FWA proposed an explosion search mechanism similar to the phenomenon of fireworks explosion [10]. Coincidentally, the positioning satisfies the proximity similarity, and the location optimization is in line with the explosion search. And this is our motivation to introduce the FWA to solve the model. However, to enhance the adaptability of explosion search mechanism, the self-adapting operators are designed. In terms of the energy efficiency, a centralized positioning scene is constructed in which the control plane collects the location parameters from the data plane and runs the algorithm. Thus, by concentrating complex operations on the resource-rich control plane, the life of the resource-constrained sensor node is prolonged, thereby achieving a win-win situation between the accuracy and power consumption of positioning.

II. Model building

Fig. 1 illustrates the centralized positioning scene of SD-WSN. The controller collects data plane location parameters through the southbound interface, including anchor node position and inter-node RSSI, and then runs the self-adapting FWA (SA-FWA) to solve the coordinates of blind nodes.

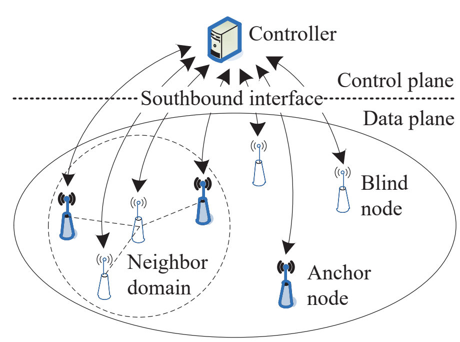

Fig. 1. The centralized positioning scene of SDWSN

Taking the above scene as the research object, the positioning area in the data plane is denoted as D. By characterizing

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the node position as a vector, the sensor node set is defined as $C = \{\vec{c}_k | k = 1, 2, \cdots, m_c\}$, $\vec{c}_k = \left\{c_k^1, c_k^2, \cdots, c_k^v\right\}$ is the k-th sensor node, m_c is the number of sensor nodes, and v is the coordinate dimension. Similarly, the anchor node set is denoted as $A = \{\vec{a}_i | i = 1, 2, \cdots, m_a\}$, $\vec{a}_i = \left\{a_i^1, a_i^2, \cdots, a_i^v\right\}$ is the i-th anchor node, m_a is the number of anchor nodes; the blind node set is defined as $B = \left\{\vec{b}_j | j = 1, 2, \cdots, m_b\right\}$, $\vec{b}_j = \left\{b_j^1, b_j^2, \cdots, b_j^v\right\}$ is the j-th blind node, m_b is the number of blind nodes. Obviously, $C = A \bigcup B$, $A \bigcap B = \varnothing$.

Definition 1 The difference of the RSSI-based ranging distance and the real geographic distance between neighboring nodes is called positioning error, denoted as d, and the calculation is shown in Eq. (1).

$$d\left(\vec{b}_j, \vec{c}_k\right) = \left|d_g\left(\vec{b}_j, \vec{c}_k\right) - d_r\left(\vec{b}_j, \vec{c}_k\right)\right| \tag{1}$$

Node $\vec{c}_k$ is located in the neighbor domain of $\vec{b}_j$. The d_r and d_g are the ranging distance and the geographic distance. The former is calculated by log-distance path loss model. The latter is characterized by Euclidean distance. The above two distances can be expressed by Eq. (2) and Eq. (3), respectively.

$$d_r\left(\vec{b}_j, \vec{c}_k\right) = d_0 \times 10^{\frac{RSSI(d_0) - RSSI\left(\vec{b}_j, \vec{c}_k\right) + X_\sigma}{10q}} \tag{2}$$

$$d_g\left(\vec{b}_j, \vec{c}_k\right) = \sqrt{\sum_{l=1}^{v}\left(b_j^l - c_k^l\right)^2} \tag{3}$$

In Eq. (2), $RSSI(\vec{b}_j, \vec{c}_k)$ represents RSSI between $\vec{b}_j$ and $\vec{c}_k$; $RSSI(d_0)$ denotes RSSI at reference distance d_0 (usually 1m); q is the path loss exponent; $X_\sigma \sim N(0, 1)$ characterizes environmental Gaussian noise.

On this basis, considering the bRSSI, the positioning mathematical model is established with the aim of minimizing the positioning error, as shown in Eq. (4).

$$\begin{cases} \min f(B) = \sum_{j=1}^{m_b}\sum_{k=1}^{m_c} \alpha \times d\left(\vec{b}_j, \vec{c}_k\right) \\ \text{s.t.} \begin{cases} RSSI\left(\vec{b}_j, \vec{c}_k\right) \neq \varnothing \\ \alpha = \begin{cases} 1 - \beta & \vec{c}_k \in A \\ \beta & \vec{c}_k \in B \end{cases} \\ \beta \in [0, 1] \end{cases} \end{cases} \tag{4}$$

In the constraints, $RSSI\left(\vec{b}_j, \vec{c}_k\right) \neq \varnothing$ limits $\vec{b}_j$ and $\vec{c}_k$ as neighbor nodes, and β is optimization factor, which characterizes the sensitivity of positioning error to inter-node RSSI. The larger the value of β, the more obvious the effect of bRSSI.

III. RSSI-based Positioning with SA-FWA

In this section, the fitness function and operators in the SA-FWA are designed, and the positioning process is given.

A. Fitness function

Multi-node positioning is essentially a multi-objective optimization problem. Therefore, we turn it into a single-objective optimization by constructing a blind node positioning matrix. Based on the matrix, the evolutionary elements in the SA-FWA are constructed, as shown in **Definition 2**.

Definition 2 Fireworks, explosion and mutation sparks are collectively referred as evolutionary elements, denoted as E, characterized by the blind node positioning matrix, namely $E = \left(\vec{b}_1, \vec{b}_2, \cdots, \vec{b}_{m_b}\right)^T = \left(b_j^l\right)_{m_b \times v}$, $l = 1, 2, \cdots, v$.

Obviously, E is a $m_b \times v$ matrix, the row vector is the blind node, and its element is the node coordinate dimension.

Combined with the model, the design of the fitness function for single-objective optimization can be expressed by Eq. (5).

$$\begin{cases} \min f(E) = \sum_{j_1=1}^{m_b}\sum_{j_2=1}^{m_b} \beta \times d\left(\vec{b}_{j_1}, \vec{b}_{j_2}\right) + \\ \qquad \sum_{j_1=1}^{m_b}\sum_{i=1}^{m_a} (1 - \beta) \times d\left(\vec{b}_{j_1}, \vec{a}_i\right) \\ \text{s.t.} \begin{cases} \vec{b}_{j_1}, \vec{b}_{j_2} \in E; E \in D \\ RSSI\left(\vec{b}_{j_1}, \vec{b}_{j_2}\right) \neq \varnothing; RSSI\left(\vec{b}_{j_1}, \vec{a}_i\right) \neq \varnothing \\ \beta \in [0, 1] \end{cases} \end{cases} \tag{5}$$

The constraints indicate that both $\vec{b}_{j_2}$ and $\vec{a}_i$ should be neighbors of $\vec{b}_{j_1}$, and $\vec{b}_{j_1}$ and $\vec{b}_{j_2}$ need to be located in D.

B. Operators

The operators includes self-adapting explosion (SE) operator, self-adapting mutation (SM) operator and selection strategy, which together affect the performance of SA-FWA.

1) SE operator: The SE operator is a concrete implementation of the explosion search mechanism. High-quality fireworks (small fitness values) could get more resources, and explosions in a small area generate a lot of sparks, which is convenient for local search. Conversely, low-quality fireworks (large fitness values) produce a small number of sparks in a large area, which facilitates the global search.

Definition 3 The operation of the fireworks adaptively generating explosion sparks is called SE operator and is defined as $\Phi : E \to E + \vec{\lambda} A_E \vec{\theta}$.

The SE operator is shifted by a polar coordinate system, $\vec{\theta}$ and $\vec{\lambda} A_E$ are polar angle matrix and polar radius matrix, respectively. $\vec{\theta} = \left(\vec{\theta}_1, \vec{\theta}_2, \cdots, \vec{\theta}_{m_b}\right)^T$, the j-th polar angle vector $\vec{\theta}_j = \left\{\cos\theta_j^1, sin\theta_j^1 \cos\theta_j^2, \cdots, sin\theta_j^1 \sin\theta_j^2 \cdots sin\theta_j^{v-1}\cos\theta_j^v\right\}$, $\theta_j^l = \text{rand}(0, 2\pi)$. The random matrix $\vec{\lambda} = (\lambda)_{v \times m_b}$, $\lambda = \text{rand}(0, 1)$. A_{E^r} is the explosion radius and is calculated by the fitness function, as shown in Eq. (6).

$$A_{E^r} = \frac{R}{\omega} \times \frac{f(E^r) - f_{\min} + \varepsilon}{\sum_{r=1}^{n}\left(f(E^r) - f_{\min}\right) + \varepsilon} \tag{6}$$

$f_{\min} = \min\left(f\left(\vec{E}\right)\right)$, $\vec{E} = \{E^r | r = 1, 2, \cdots, n\}$ is the fireworks swarm, n is the size of $\vec{E}$; R is the communication radius of the node; ε is the machine precision, to avoid the operation of zero division; ω is the self-adapting search factor, and can be obtained by Eq. (7).

$$\omega = \omega_{\min} + (\omega_{\max} - \omega_{\min}) \times (\gamma + \varepsilon)^{-1} \tag{7}$$

The γ represents the evolution efficiency of SA-FWA, $\gamma \geq 1$. The $\omega_{\max}$ and $\omega_{\min}$ are the maximum and minimum values of ω, respectively. Obviously, $\omega \in [\omega_{\min}, \omega_{\max}]$,

$\omega \propto \gamma^{-1}$. Therefore, when the algorithm evolves faster, ω could effectively speed up the global search, and vice versa, quickly improve the local search accuracy.

According to the SE operator, fireworks could produce a specified number of sparks within the explosion radius, and the number of explosion sparks generated by the r-th fireworks E^r can be expressed by Eq. (8), $f_{\max} = \max\left(f\left(\vec{E}\right)\right)$.

$$S_{E^r} = \omega \times m_b \times \frac{f_{\max} - f(E^r) + \varepsilon}{\sum\limits_{r=1}^{n}(f_{\max} - f(E^r)) + \varepsilon} \tag{8}$$

Since S_{E^r} is supposed to be an integer and the fireworks with a large fitness value should be prevented from generating too little sparks, S_{E^r} is corrected to $\widehat{S}_{E^r}$, as shown in Eq. (9).

$$\widehat{S}_{E^r} = \begin{cases} \operatorname{ceil}(h \times \omega \times m_b), & S_{E^r} < h \times \omega \times m_b \\ \operatorname{round}(S_{E^r}), & S_{E^r} \geq h \times \omega \times m_b, 0 < h < 1 \end{cases} \tag{9}$$

2) SM operator: As a supplement to the SE operator, the SM operator could enhance the diversity of the fireworks swarm and prevent the algorithm from falling into local optimum. Therefore, the principle of mutation is that the smaller fitness value of fireworks, the larger mutation radius, and the more mutation sparks.

Definition 4 The operation of the fireworks adaptively generating mutation sparks is called SM operator and is defined as $\Gamma : E \to E + A'_E \vec{e}$.

The SM operator is shifted by a rectangular coordinate system. The Gaussian mutation matrix $\vec{e} = (e \times \operatorname{round}(\operatorname{rand}(0,1)))_{m_b \times v}$, $e \sim N(1,1)$; A'_E is the mutation radius, as shown in Eq. (10).

$$A'_{E^r} = R \times \frac{f_{\max} - f(E^r) + \varepsilon}{\sum\limits_{r=1}^{n}(f_{\max} - f(E^r)) + \varepsilon} \tag{10}$$

According to SM operator, the fireworks could generate a specified number of sparks within the mutation radius. The number of mutation sparks S'_{E^r} generated by E^r can be expressed by Eq. (11).

$$S'_{E^r} = \delta \times \omega \times m_b \times \frac{f_{\max} - f(E^r) + \varepsilon}{\sum\limits_{r=1}^{n}(f_{\max} - f(E^r)) + \varepsilon} = \delta S_{E^r} \tag{11}$$

$\delta \in [0,1]$ is the mutation coefficient, which is used in conjunction with ω for the adjustment of S'_{E^r}. Similarly, it is corrected as $\widehat{S'}_{E^r} = \operatorname{ceil}(S'_{E^r})$. Note that to prevent SA-FWA from falling into local optimum when enhancing the adaptive search performance, ω only acts on the number of mutation sparks without affecting the mutation radius.

It should be noted that the sparks produced by the above operators may exceed the feasible domain D. Therefore, when the l-th coordinate dimension b_j^l is out of bounds, the b_j^l is remapped into D by Eq. (12).

$$b_j^l \to b_{\min}^l + \left|b_j^l\right| \% \left(b_{\max}^l - b_{\min}^l\right) \tag{12}$$

The $b_{\max}^l$ and $b_{\min}^l$ are the maximum and minimum values of the l-th dimension in D, and "%" is the modulo operator.

3) Selection strategy: After the sparks are generated, some excellent elements will be evolved into the next generation of fireworks swarm. According to the elite strategy, the elite corresponding to $f_{\min}$ in the evolutionary elements set K will evolve. Then, the remaining $n-1$ elements are generated using a roulette strategy. In order to enhance the evolutionary effect, the probability of being selected in roulette is determined by the degree of element crowding, and the probability $p(E^r)$ can be expressed by Eq. (13). Obviously, the denser elements, the smaller probability.

$$p(E^r) = \frac{\sum\limits_{\vec{b}_s \in K} d_g\left(\vec{b}_r, \vec{b}_s\right)}{\sum\limits_{\vec{b}_r \in K}\sum\limits_{\vec{b}_s \in K} d_g\left(\vec{b}_r, \vec{b}_s\right)} \tag{13}$$

C. Positioning process

Fig. 2 shows the positioning process, including three phases of parameter acquisition, model solution and result output.

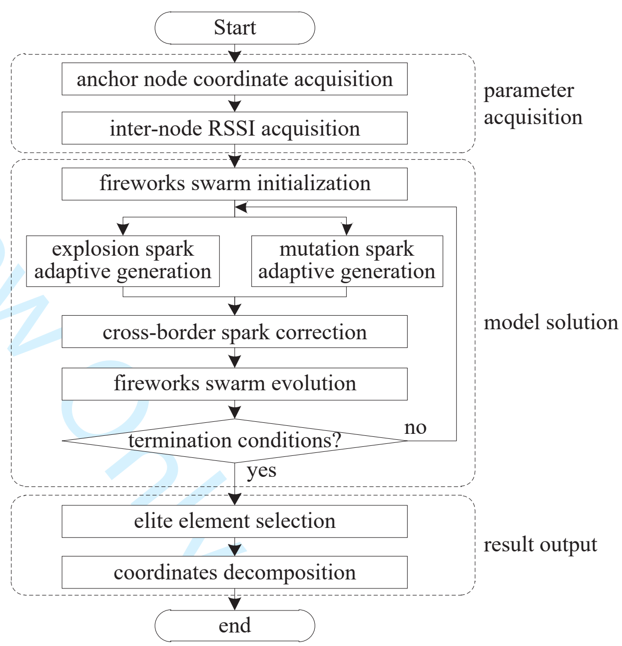


Fig. 2. The process of RSSI-based positioning with SA-FWA

In Fig. 2, The parameters acquired by the control plane include anchor node coordinates and inter-node RSSI. In the model solution, the blind nodes randomly dock neighbor anchor nodes when the fireworks swarm is initialized. If there is no feasible anchor node, the blind node randomly bind itself to the neighbor blind node. The termination condition of SA-FWA is that the elite fitness value is unchanged for g consecutive times. Finally, when the positioning result is output, the position matrix of the elite outputted by the SA-FWA is parsed into the coordinates of each blind node.

IV. Experiment and Result Analysis

According to the SA-FWA, we conduct simulation experiments based on the open dataset provided in [11].

TABLE I
THE RELEVANT PARAMETERS AND VALUES

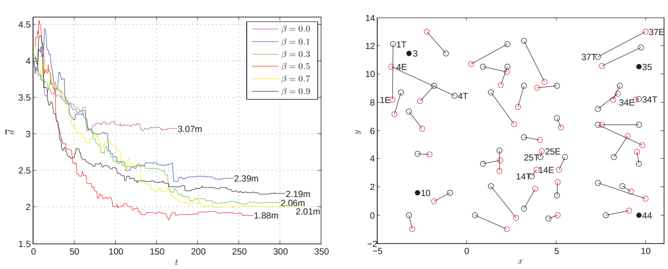
Parameter	Value	Parameter	Value	Parameter	Value
R	30m	v	2	ω_{max}	25
q	2.30	n	5	ω_{min}	1
d_0	1m	δ	0.30	h	0.20
$RSSI(d_0)$	-37.47dBm	ε	10^{-6}	g	10

A. Experimental deployment

The open dataset collects RSS data between 44 sensor nodes that are interconnected in an office environment. Referring to the setting of [11], the sensor nodes No. 3, No. 10, No. 35 and No. 44 are selected as anchor nodes, and the remaining nodes are regarded as blind nodes, that is, $m_a = 4$, $m_b = 40$. We set D to a rectangular area with vertex coordinates of $(-5,-2)$, $(-5,14)$, $(11,-2)$, $(11,14)$, respectively. In addition, γ is characterized by the change of the elite fitness value, so $\gamma = \left(f_{min}^{t-1} - f_{min}^{t}\right) + 1$ $(t \geq 2)$, t is the iteration number. The other relevant parameters and values are given in Table 1.

B. Experimental result

According to the deployment, the influence of β on the average positioning error $\overline{d}$ is analyzed, and the optimal positioning result is given. The $\overline{d}$ is characterized by the root mean square (RMS), that is, $\overline{d} = \sqrt{\sum_{E} d^2/m_b}$. For each β, the experiment was performed 10 times independently, and the final result was taken as the one closest to the mean. The experimental results of $\overline{d}$ are shown in Fig. 3.



(a) $\overline{d}$ vs. β (b) $\overline{d}$ = 1.88m

Fig. 3. The experimental results of $\overline{d}$

Fig. 3(a) shows the evolution of $\overline{d}$ with t under different β. For all β, $\overline{d}$ exhibits a decreasing trend in iterations ($\overline{d}$ occasionally increases slightly due to measurement errors in RSSI), and ends at different values when fitness values are the same for 10 consecutive times. Obviously, when β equals 0.3, 0.5 and 0.7, $\overline{d}$ converges to 2.06m, 1.88m and 2.01m respectively, which are significantly better than the average positioning error of 2.18m obtained in [11]. It should be noted that when $\overline{d}$ is optimal, $\beta = 0.5$, that is, the sensitivity of the model to RSSI between all nodes is the same, which is consistent with the homogeneity of the nodes in the dataset.

Fig. 3(b) presents the positioning results of $\overline{d}$ = 1.88m, where "T" and "E" represent the True and Estimated locations of the node. It can be seen that the proportions of nodes with $\overline{d}$ < 3.0m, $\overline{d}$ < 2.0m and $\overline{d}$ < 1.0m are 90%, 70% and 30%, respectively. The nodes with the smallest error are NO.34 (0.19m), NO.25 (0.41m), and NO.14 (0.53m), and the largest ones are NO.4 (4.08m), NO.1 (3.94m), and NO.37 (3.21m). Coincidentally, the positioning errors of nodes NO.4 and NO.1 in [11] are also large, and it is speculated that there may be a large deviation in the RSSI measured by these nodes.

In order to further verify the contribution of the bRSSI to the model, the experiment was carried out with the traditional idea without considering the bRSSI ($\beta = 0.0$). It can be seen from Fig. 3(a) that $\overline{d}$ = 3.07m, and it is obviously inferior to the cases where $\beta > 0.0$. At the same time, the evolution efficiency of the algorithm is also low, and the fitness value does not decrease after 165 iterations. In summary, the full use of the bRSSI significantly improves the performance of the model and effectively reduces the positioning error.

V. CONCLUSION

Aiming at the dilemma of SDWSN positioning, a centralized scene is designed to reduce power consumption. In terms of improving accuracy, this paper establishes a mathematical model to minimize the positioning error by introducing bRSSI, and designs an optimization factor to adjust the sensitivity of the error to the inter-node RSSI. Considering that the location optimization is consistent with the explosion search mechanism, a single-target SA-FWA is used to solve the model based on the blind node positioning matrix. Finally, the average positioning error of 1.88m, which is currently optimal, is achieved by experimenting with the open dataset.

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