TDOA Location Based on Pigeon-Inspired Optimization Algorithm in WSNs

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Abstract. The pigeon-inspired optimization (PIO) algorithm belongs to a novel type of meta-heuristic algorithm, which has manifested in many aspects. Wireless sensor networks (WSNs) are a type of information acquisition technology and have been widely used as a new platform for information acquisition and processing. Due to the limited environment and hardware conditions for dealing with a large number of data sets to be processed, this paper uses the PIO algorithm to optimize the positioning method of time difference of arrival (TDOA) which a positioning method in the WSNs. Experimental results show that PIO can improve TDOA higher positioning accuracy and better convergence.

Keywords: Meta-heuristic algorithm · Pigeon-inspired optimization · Time difference of arrival · WSNs

1 Introduction

With the advent of the information age, the amount of data has changed qualitatively. When we are processing these large amounts of data, some original methods are not applicable. Those original methods are likely to cause problems such as low accuracy and long algorithm execution time. Some methods are the most direct way to solve the above problem.

The PIO algorithm is a meta-heuristic algorithm that has appeared in recent years proposed by Duan and Qiao in 2014 [1–3]. The PIO algorithm is to model the behavior of the pigeons returning home. The update and iterative process of the pigeons is an operator that considers two stages. In daily life, pigeons are considered to be a intelligent creatures, and the research on the behavior of individual pigeons has achieved fruitful results. For example, pigeons have the function of consciousness.

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WSNs are an important method of information transmission [4–7]. TDOA is a positioning technology in WSNs. It belongs to obtaining the distance between an unknown node with different known nodes. When TDOA locates WSNs, using the original algorithm for positioning will cause poor positioning accuracy and sometimes the algorithm cannot get acceptable convergence. PIO is used for estimation in location. The experiment results show that PIO algorithm are used in this paper and it have high accuracy and a small error in positioning of TDOA for WSNs positioning.

The rest of this paper is arranged as follows, Sect. 2 introduces the detailed information for the TDOA and PIO, additionally, the model of TDOA descriptions are given. Section 3 shows how to use the improved model to improve the accuracy of TDOA locations. Section 4 presents the final conclusions and the outlooks for future work based on the results of this paper.

2 Related Work

2.1 Time Difference of Arrive (TDOA)

The TDOA algorithm calculates the corresponding distance according to the time difference between the two signals with different speeds to the unknown node [8–12]. First, node A transmits ultrasonic waves and radio frequency signals together. Due to the different transmission speeds of these two signals, their time to reach node B is also different [13–17]. When node B receives these two signals, it records the arrival time of both, then takes the time difference, and calculates the distance connection between the mobile station and base station according to the transmission speed of the two signals. Suppose the radio frequency signal rate is represented by v_1, the ultrasonic rate is represented by v_2, the arrival times are T_1 and T_2, and the distance between nodes A and B is d, as shown in the Fig. 1.

$$d = \left| \frac{T_2 - T_1(v_1 * v_2))}{v_1 - v_2} \right|, \tag{1}$$

The TDOA algorithm has high positioning accuracy and small error [18–23]. However, it can be seen from the calculation process of the algorithm that TDOA has the same high time requirements. The propagation of wireless signals may also receive noise interference. Changes in the environment will also affect the accuracy of the algorithm. There are two types of devices for transmitting signals. When the anchor node is in the working state, the energy consumption of the node is also relatively large.

$$\begin{aligned} R_{i,1} &= cd_{i,1} = R^0_{i,1} + cn_{i,1} = R_i - R_1 + cn_{i,1} \\ i &= 2, 3, ..., M, \end{aligned} \tag{2}$$

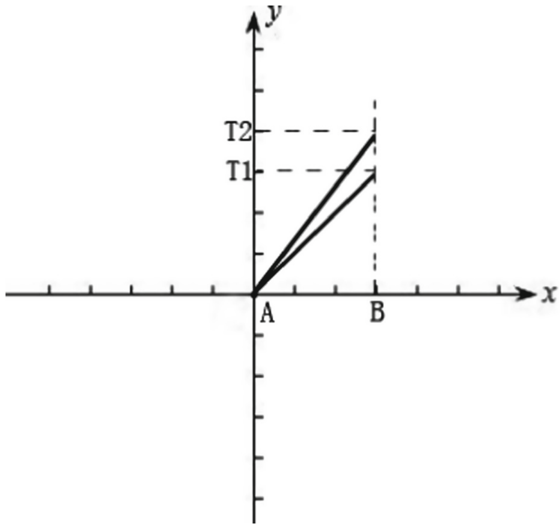

Fig. 1. TDOA positioning distance between A and B

where, c is transmission rate, $d_{i,1}$ is TDOA measure distance values, $cn_{i,1}$ is noise added when TDOA is measured, for convenience, the noise is considered to be white Gaussian noise satisfying the variance of α^2 of the independent and identical distribution.

Suppose there are M anchor nodes randomly placed in a two-dimensional plane. The estimated coordinates of the unknown nodes after successful positioning are represented by (x, y), this right coordinates of the i-th anchor node are represented by (X_i, Y_i), R_i represents the anchor. The distance between unknown position i and this anchor node is calculated using real azimuth coordinates. $R^0_{i,1}$ represents the actual distance difference between any labeled anchor node $i(i \neq 1)$ which is calculated using azimuth coordinates, $R_{i,1}$ is a measure of distance and c is the radio wave transmission speed, as shown in the Fig. 2.

$$\begin{aligned} R_i &= \sqrt{(X_i - x)^2 + (Y_i - y)^2)} \\ R_i^2 &= (X_i - x)^2 + (Y_i - y)^2 \\ &= k_i - 2x_i x - 2y_i y + x^2 + y^2, \end{aligned} \tag{3}$$

$$\begin{aligned} R_{i,1} &= c\tau_{i,1} \\ &= R_i - R_1 \\ &= \sqrt{(X_i - x)^2 + (Y_i - y)^2)} - \sqrt{(X_1 - x)^2 + (Y_1 - y)^2)}, \end{aligned} \tag{4}$$

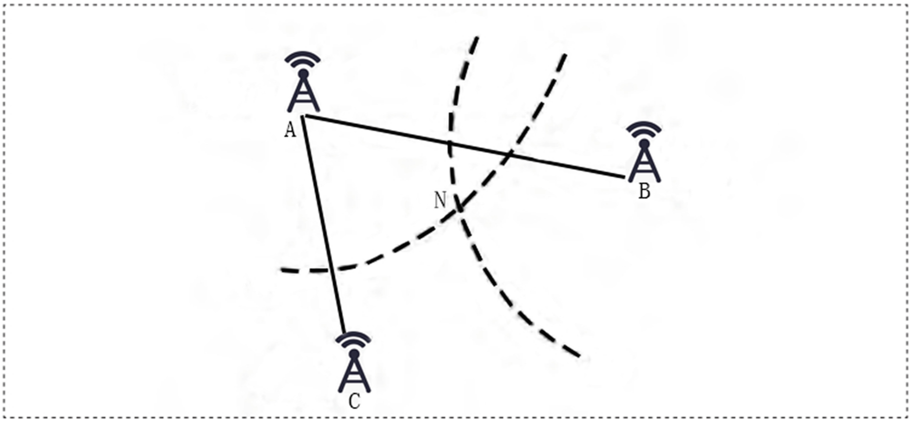

Fig. 2. TDOA positioning principle

In the Eq. (3) and Eq. (4), $K_i = x_i^2 + y_i^2$. And $R_{i,1}$ represents a distance difference, $\tau_{i,1}$ is value of TDOA measurement. From Eq. (3) and Eq.(4), we can get the following equation:

$$R_i^2 = (R_{i,1} + R_1)^2, \tag{5}$$

Taking Eq. (5) back to Eq. (3) and it can gives below equation.

$$\begin{aligned} R_{i,1}^2 &= 2R_{i,1}R_1 + R_1^2 \\ &= K_i - 2x_i x - 2y_i y + x^2 + y^2, \end{aligned} \tag{6}$$

Next, combining Eq. (5) and Eq. (6), we can gives the following formula:

$$R_{i,1}^2 + 2R_{i,1}R_1 = K_i - 2x_{i,1}x - 2y_{i,1}y - K_1, \tag{7}$$

In Eq. (7), $x_{i,1} = x_i - x_1$, $y_{i,1} = y_i - y_1$, x, y, K_1 are unknown variables, in the next formula, the noise effect is added.

$$\begin{aligned} R_{i,1} = &\sqrt{(X_i - x)^2 + (Y_i - y)^2)} - \sqrt{(X_1 - x)^2 + (Y_1 - y)^2)} + cn_{i,1} \\ &i = 2, 3, ..., M, \end{aligned} \tag{8}$$

$$\begin{aligned} \Delta R &= [R_{2,1}, R_{3,1}, ..., R_{m,1}]_{(M-1)*1}^T \\ R_{i,1} &= [R_2, R_3, ..., R_M]_{(M-1)*1}^T \\ R_1 &= [R_1, R_1, ..., R_1]_{(M-1)*1}^T \\ N &= [n_{2,1}, n_{3,1}, ..., n_{M,1}]_{(M-1)*1}^T, \end{aligned} \tag{9}$$

Combining Eq. (8) and Eq. (9) gives the following formula:

$$\Delta R = R_i - R_1 + cN$$
$$= \begin{bmatrix} \sqrt{(X_2-x)^2+(Y_2-y)^2} - \sqrt{(X_1-x)^2+(Y_1-y)^2} \\ \sqrt{(X_3-x)^2+(Y_3-y)^2} - \sqrt{(X_1-x)^2+(Y_1-y)^2} \\ .... \\ \sqrt{(X_M-x)^2+(Y_M-y)^2} - \sqrt{(X_1-x)^2+(Y_1-y)^2} \end{bmatrix} + cN \tag{10}$$

In this article, set $M > 3$, the use of maximum likelihood estimation method to estimate the unknown node coordinate is the maximum, because $R_{i,1}$ obeys the Gaussian distribution with $R_{i,1}$ mean of $(R_i - R_1)$ and α^2 variance, and each separate value is measured, and therefore the likelihood function is obtained:

$$\prod_{i=1}^{M-1}[\frac{exp^{\frac{(\Delta R-R_i+R_1)^2}{-2\sigma^2}}}{\sqrt{2\pi\sigma}}] == [[\frac{1}{\sqrt{2\pi\sigma}}]^{M-1}exp[\frac{(\Delta R-R_i+R_1)^2}{-2\sigma^2}]], \tag{11}$$

Solving the likelihood function is maximum frame of reference value, which is equivalent to solving
$(x,y) = arg[max[exp[\frac{(\Delta R-R_i+R_1)^2}{-2\sigma^2}]]]$.

$$C = R_i - R_1 = \begin{vmatrix} a_1 \\ a_2 \\ ... \\ a_{M-1}, \end{vmatrix} \tag{12}$$

In the process of constructing the hyperbolic model, since the difference between the distance from the point on the hyperbola to the two focal points is a fixed value, this fixed value is set to Eq. (12) in this article.

$$(x,y) = \underset{(x,y)\in S}{arg}[min(\Delta R - C)^T(\Delta R - C)], \tag{13}$$

Solving the minimum value of the nonlinear function of Eq. (13) can get the estimated value of the unknown node, S is expressed as a range space of cN floating up and down the points on the hyperbola. It is very difficult to use the analytical method. In this paper, the method of PIO coordinate is used to solve this nonlinear function, and the estimated value of unknown nodes is determined.

2.2 Pigeon-Inspired Optimization

In the target search space, the PIO algorithm first generates a population of N particles representing potential problem solutions, and then the particles in the population follow the best particles in each generation to move continuously in the target space. Individuals in the population gradually seek out the optimal solution on the target space by continuously iterating, in a population the i-th pigeon is represented as a vector in the D-dimensional inter-space. Then in this paper uses Eq. (14) and Eq. (15) on the behalf of position and velocity of the i-th pigeon in the population, and $gBest$ represents the best particle in the population that has been searched so far [24–27].

$$Pos_i = [pos_{i,1}, pos_{i,2}, ..., pos_{i,D}], \tag{14}$$

$$Vel_i = [vel_{i,1}, vel_{i,2}, ..., vel_{i,D}], \tag{15}$$

During the iterative process of the PIO, it consisted of two iterative stages, including the map and compass operator, and landmark operator. The first operators are the way finding methods used by pigeon groups far away from home. The pigeon uses magnetic objects to sense the magnetic field on the earth, and then it can form a map in the pigeon's brain, and then use the sun's height as a compass to adjust the pigeon's flight direction. As the pigeon approached its destination, it became less dependent on magnetic objects and the sun, and instead used landmark operators for navigation. The second stage of the pigeon is to use the landmark operator for navigation. When the pigeon is near the destination, the dependence on the landmark near the destination becomes greater. If the pigeon knows the landmark of the destination, it will fly immediately to the destination, or else just follow close behind the pigeons in the population who know their destination [28–31].

In the PIO, the iterative criteria for the flock in the first phase of the first operator of PIO are shown in Eq. (16) and Eq. (17). The iterative criteria for the pigeons in the second phase of PIO is shown in Eq. (18)–Eq. (21).

Map and compass operator: where R is the first phase factors, and ϕ_1, ϕ_2, ϕ_3 is a stochastic number among 0 and 1. t is the iteration number of the PIO.

$$vel_i^{t+1} = e^{-R\times t} \times vel_i^t + \phi_1 \times (pos_{gBest} - pos_i), \tag{16}$$

$$pos_i^{t+1} = \phi_2 \times pos_i^t + \phi_3 \times vel_i^{t+1}, \tag{17}$$

Landmark operator: pos_{center}^{t-1} is the landmark operator. The pigeons with the ability to know the way in the entire population. Other pigeons without the ability to learn the way follow the pigeon with the ability to learn the way. ϕ_4 is a stochastic number among 0 and 1.

$$No^{t-1} = \frac{No^{t-2}}{2}, \tag{18}$$

$$pos_{center}^{t-1} = \frac{\sum_{i=1}^{No^{t-1}} pos_i^{t-1} \times F(pos_i^{t-1})}{No^{t-1} \times \sum_{i=1}^{No^{t-1}} F(pos_i^{t-1})}, \tag{19}$$

$$pos_i^t = pos_i^{t-1} + \phi_4 \times (pos_{center}^{t-1} - pos_i^{t-1}), \tag{20}$$

$$F(pos_i^{t+1}) = \begin{cases} \frac{1}{fitness(pos_i^{t+1})+\theta} \\ fitness(pos_i^{t+1}), \end{cases} \tag{21}$$

3 Experiments for TDOA in WSNs Problem

The TDOA positioning algorithm determines the location of a mobile station (MS) by measuring the propagation time difference of radio waves traveling from an MS to multiple base stations (BS). The system of hyperbolic equations composed of multiple TDOA measurements is nonlinear and difficult to solve. Many meta-heuristic algorithms have been proposed to solve the above-mentioned nonlinear and difficult problem. The PIO algorithm determines the coordinate location of the MS based on the sector in which the MS is located, and then uses the inverse of the likelihood function as the individual fitness value to select the good individual, determines the crossover rate and the mutation rate, and uses the binary number to perform the chromosome analysis. The code searches the mobile station located within the coordinate range determined by the service desk. Initialize the positioning of the mobile station, compare the final positioning result with TDOA [32–35].

The following problems may occur during the positioning process:

1. Signal impairment: the distance measurement information for indoor positioning is the distance measured under the condition of line-of-sight. If it is not the line-of-sight, such as an obstacle in the middle or it reaches by reflection, it will lead to a longer reception time. The measured distance becomes larger.
2. Base station coordinates error: the measured coordinates are relative to the anchor coordinates of the BS. If the measured coordinates values are wrong, then our positioning data is meaningless.
3. Clock synchronization error: each base station's clock will have a slight gap, but if the gap is 1 ns, there will be a 30 cm error, so if we can synchronize the time of all base stations in the system, we can further improve the positioning accuracy.

Operating environment windows10 i5-8500 3.00 GHz experiment is running on the CPU and 24 GB of memory. The parameters of the PIO algorithm are set to R as 0.2, and the maximum number of evaluations is 10000. The coordinates of the Mobile station are set to (0,0), and the coordinates of the ten Base Stations are set to (50,10) (10,100) (−70,0) (4,−15) (100,−15) (38,54) (21,−32) (15,97) (12,32) (−12,−21).

It can be seen from the Fig. 3, with the continuous increase of noise, there will be an obvious jumping point in TDOA using the least-squares method to solve the problem at 0.4–0.6. When using the PIO and PSO algorithm to solve, although the mean variance will increase slowly, it is very satisfactory compared to using the least-squares method. The PIO performs better than PSO algorithm.

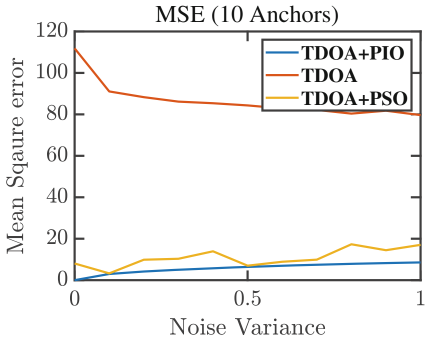

Fig. 3. TDOA positioning principle

4 Conclusion

This paper uses the PIO algorithm to solve the positioning problem of TDOA in WSNs. TDOA is a highly non-linear and realistic problem. The passive positioning method PIO algorithm based on TODA can effectively avoid the stability and accuracy of the positioning results. The realization result proves that the algorithm proposed in this paper can get closer to the optimal solution faster than the traditional solution, which is suitable for solving the positioning problem of wireless sensor networks. The final result proves that it will also perform well in comparison. The proposed method may further improve the efficiency by adopting the fast search algorithms [36–38].

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