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An Efficient TDOA and GROA Localization Mechanism Based on GSO Algorithm with Flight Theory

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Abstract. The positioning technology is of vital importance in Wireless Sensor Networks (WSNs), and its accuracy based on particle swarm optimization (PSO) is low. We propose an efficient time differences of arrival (TDOA) and gain ratios of arrival (GROA) localization algorithm with glowworm swarm optimization algorithm based on flight mechanism (Levy-GSO) for WSN in this paper. First, an improved positioning equation is introduced based on TDOA and GROA positioning model. And solve the equation by using correction two-step weighted least squares source localization method (TSWLS). To solve the nonlinear relationship between positioning equation and the target location by introducing the auxiliary variable and doing pseudo linear operation of nonlinear equation. Second, develop the GSO algorithm with flight mechanism to find the optimal solution under the same convergence speed and precision. Finally, test the proposed algorithm performance of ranging error, the number of reference nodes, Gaussian random variable variance and the root mean square error(RMSE). The simulation results indicate that the proposed localization mechanism has relative higher and stable localization accuracy compared with TDOA algorithm.

Keywords: flight mechanism, gain ratios of arrival (GROA), glowworm swarm optimization (GSO), least squares, particle swarm optimization (PSO), time differences of arrival (TDOA)

1 Introduction

1.1 Research Background

Node localization occupies an important position in the whole WSN, especially in the event observation, target tracking and network reconfiguration [1-2]. First, it is meaningful that the data collected by sensor nodes with their location information. For example, when we get a temperature value, it would be practical value if we know where it from. Second, node self-positioning can be applied in external target localization, tracking and improve the efficiency of routing.

The common passive location method is to use measurement parameters such as time of arrival (TOA), time difference of arrival (TDOA), concatenated), angle of arrival (AOA) and their combination [3]. If there is relative motion between target and receiving sensor, the frequency of arrival (FDOA) information can also be used for target localization. In recent years, with the development of technology, people gradually began to focus on the target localization using signal information from different receiving station in energy domain. The energy intensity from different receiving sensors is inversely proportional to the distance from the sensor to the signal [4]. It can achieve localization based on signal strength difference from different receiving sensors. The popular positioning methods are RSSI (the Receive Signal Strength Indicator) [4-7] and GROA (Gain the wire of Arrival). RSSI positioning technology has been widely applied in WSN due to the merits of low power and low cost. The theory of

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RSSI is to realize the node location by signal strength from the known anchor nodes, which is not satisfied in the passive location. But the GROA positioning method develops the principle of inversely proportional relationship between signal amplitude and propagation distance. The GROA method is more suitable for the passive location compared with RSSI.

1.2 The Related Work

Over the past decades, some improved RSSI algorithms were proposed aiming at achieve accurate localization. Chen and Yuan analyzed the factors of weather and obstacles in indoor positioning and presented a fuzzy algorithm based on RSSI technology [8]. It provided a more accurate distance and improved the accuracy of path loss model. Kaya and Alkar developed an adaptive filtering RSSI technology, which solves the questions of uneven nodes distribution and packet loss ratio [9]. It reduces the positioning error obviously by the reliable RSSI values. Zhi and Hui used RSSI values obtained by median data pre-processing method and calculated the estimated distance of unknown node based on weighted centroid algorithm [10]. They found that their system has lower positioning error because the results are more reliable after pre-processing. Hua and Di focused on the triangle centroid localization algorithm and analyzed information of two reference beacon nodes [11]. The algorithm adopted the reasonable communication distance to effectively improve the node positioning accuracy. Qian, Guang and Jun process the statistical data to study the relationship between measured distance and predicated distance, and builds t he probabilistic annular intervals of anchor nodes [12].

The GROA algorithm is firstly proposed by Ho and Ming [13]. They put forward passive location by using two step weighted least squares (TSWLS) with the GROA and TDOA measurement information at the same time. And Benjian, Zan and Yunmei point out that GROA plays a key role on the improvement of positioning accuracy in the hybrid system with the decrease of signal bandwidth [14]. On the basis of Benjian et al. [14], Benjian, Zan and Pengwu gives TDOA and GROA two step weighted least square passive location under the condition of sensor location error [15]. And they point out that GROA positioning information require the accurate environmental coefficient. Therefore, Benjian et al. gives the BiasRed and BiasSub two deviation reduction algorithms to promote TDOA and GROA joint positioning accuracy [15].

The firefly optimization algorithm (GSO) is a kind of evolutionary swarm intelligence computation method and is also a kind of algorithm which is based on the iterative algorithm from the random solution [16-19]. The firefly algorithm is based on the observation of the activities of the firefly cluster. The individual information is shared in groups, so that the whole group's activities rely on the strength of the group to solve the problem. When one of the individual has to find the target, the individual will emit light to attract nearby firefly to close. Then the most individual will be selected from its close, after reaching the target point. The GSO algorithm is similar with other evolutionary algorithms, which can be used to solve the equation optimization problem. For example, the multivariate function optimization problem. A lot of theoretical and experimental research results show that the GSO algorithm in solving the problems of the practical optimization, which achieves the better results. Nowadays, GSO algorithm was successfully applied to multi-objective optimization, automatic target detection, decision-making scheduling and other fields.

Based on the above analysis, this paper proposes the joint GROA time TDOA location algorithm based on GSO algorithm with the flight mechanism (Levy-GSO) to reduce the sensor localization errors based on RSSI and solve the problem of robustness. This paper mainly considers the existed position error of receiver senor and the problem of positioning results are susceptible to interference, which develops TDOA and GROA field positioning information to co-location signal source. Firstly, the algebraic closed solution of correction two-step weighted least squares algorithm based on the typical positioning model is proposed. Then the method of the nonlinear equation of pseudo linear is used to solve the pseudo linear equations to obtain the location of the object information, which is a good way to solve the problem of nonlinear relationship between target position and location equation. Secondly, aiming to optimize the positioning equation in first step, this paper proposes an improved glowworm algorithm introducing the flight mechanism. The improved Levy-GSO not only helps to jump out of the office of the optimal, but also can get better convergence when particles are near the global optimal value. Finally, the feasibility and effectiveness of the mechanism proposed in this paper are verified by the numerical simulation and experiment of MATLAB. The results show that the proposed algorithm has good robustness and high positioning accuracy compared with TDOA algorithm under the condition of different parameters.

2 The Localization Model of TDOA and GROA

2.1 The Definition of TDOA

The received signal of receiving sensor by is defined as:

$$\begin{aligned} x_1(t) &= s(t) + \xi_1(t) \\ x_i(t) &= \frac{1}{g_{i1}} s(t - \tau_{i1}{}') + \xi_i(t) \end{aligned} \quad (1)$$

Where $i = 2,3,\cdots M$. $s(t)$ is target emission signal, $\xi_i(t)$ is the signal noise of i receiving sensor. $x_i(t)$ is the receiving signal of i sensor. In this paper, we put the first sensor be reference node.

$\tau_{i1}{}'$ is defined as arrival time difference (TDOA) of i sensor signal, the measuring time difference value of M sensor is $\tau' = [\tau_{21}{}', \tau_{31}{}', \cdots, \tau_{M1}{}']^T$.

We get the distance difference arrival (RDOA) of the i sensor and the 1 sensor from the time difference value multiplies to signal propagation speed c . The distance between i sensor and the target can be represented as:

$$r_i' = \left\| u' - s_i' \right\| \quad (2)$$

Where "$\|*\|$" means euclidean distance, $i = 2,3,\cdots M$.

The distance difference between i sensor and the first sensor is:

$$r_{i1}{}' = r_i' - r_1' = c\tau_{i1}{}' = r_{i1} + \Delta r_{i1} \quad (3)$$

Where c is the signal propagation speed, $\tau_{i1}{}'$ is the actual time difference between i sensor and the first sensor, r_{i1} is calculated distance value, Δr_{i1} is the measuring error of distance difference.

In simple, $r' = [r_{21}{}', r_{31}{}', \cdots, r_{M1}{}']^T$, $r = [r_{21}, r_{31}, \cdots, r_{M1}]^T$, $\Delta r = [\Delta r_{21}, \Delta r_{31}, \cdots, \Delta r_{M1}]^T$. The equation of measuring distance difference is:

$$r = r' + \Delta r \quad (4)$$

Suppose time difference error requires the Gaussian distribution of zero mean, the covariance matrix is $E[\Delta r \Delta r^T] = Q_r$.

2.2 The Definition of GROA

g_{i1} is the gain ratio of receiving signal from i sensor relative to the first sensor in formula (1). According to the acoustics and microwave theory, the signal transmission loss factor is in proportion to n power of distance between the i sensor and 1 sensor. We suppose n is the constant value of 1. The measuring gain ratio of M sensor is $g' = [g_{21}{}', g_{31}{}', \cdots, g_{M1}{}']^T$. The GROA between i sensor and the first sensor is:

$$g_{i1}{}' = r_i' / r_1' \quad (5)$$

Where c is the light speed, r_i' is the real distance between the target and i sensor. And GROA parameters can be written as a vector form: $g = [g_{21}, g_{31}, \cdots, g_{M1}]^T$, $\Delta g = [\Delta g_{21}, \Delta g_{31}, \cdots, \Delta g_{M1}]^T$. Furthermore, the measuring equation of arrival gain ratio is:

$$g = g' + \Delta g \tag{6}$$

Where g_{i1} is the real GROA value, Δg_{i1} is the GROA measuring error. Assuming g_{i1} and Δg_{i1} obey the zero mean Gaussian distribution, and independent of the time difference error. The covariance matrix is $E[\Delta g \Delta g^T] = Q_g$.

3 The TDOA and GROA Localization based on Levy-GSO

This paper mainly studies the problem of time difference (TDOA) and gain ratio (GROA) joint localization. Due to the nonlinear relationship between positioning equation and the target location, it is difficult to solve the actual target location directly. There are two categories for the solution of nonlinear equation: (1) The Taylor series expansion method. It gives up the second order and higher term to obtain the linear equation, which expands the nonlinear equation near the actual target location. Finally, we approach the true location of target after multiple iterations [20]. (2) We solve the nonlinear equation to obtain the target location by introducing the auxiliary variables [21]. The first method often requires a precise iterative initial value, and the typical algorithms are Newton iteration method [2], quasi-Newton iteration method [22] and so on. However, the second method has closed solution under certain conditions and there is no divergence problem. The typical algorithms are two-step weighted least-squares algorithm (TSWLS) [23], the constrained weighted least squares algorithm (CWLS) [24], constrained total least squares algorithm (CTLS) [25]. Among them, the TSWLS algorithm has low computational complexity, which is widely used. This paper puts forward TDOA and GROA joint localization algorithm based on the above ideas, and develops the glowworm optimization algorithm based on flight mechanism. Last, we verify the performance of proposed algorithm compared with traditional TDOA algorithm by using the simulation tool.

3.1 Positioning Distribution

Fig. 1 is the joint location map of TDOA value from receiving sensor and GROA value of received signal. We assume that the object positioning vector is $u' = [x', y', z']^T$, the number of receiving sensors is M. The actual position of i sensor is $s_i' = [x_i', y_i', z_i']^T$, $i = 1, 2, \cdots M$, "$[*]^T$" means transpose, and the actual position of i sensor is $s_i = [x_i, y_i, z_i]^T$.

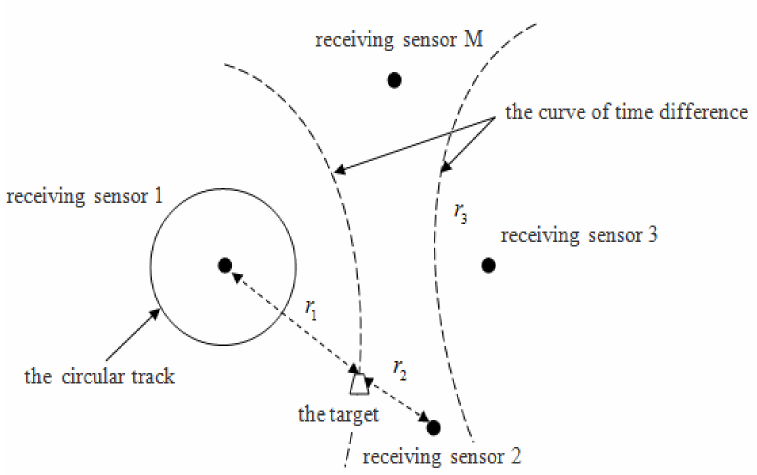

Fig. 1. Positioning distribution

Where $s' = [s_1'^T, s_2'^T, \cdots, s_M'^T]^T$, $s = [s_1^T, s_2^T, \cdots, s_M^T]^T$ and $\beta' = s'$, $\beta = s$. Let receiving sensor positioning error be $\Delta s = [\Delta s_1^T, \Delta s_2^T, \cdots, \Delta s_M^T]^T$, where $\Delta s_i = s_i - s_i'$. Assuming that $\Delta\beta$ meet the Gaussian distribution of zero mean, and the covariance matrix is $E[\Delta\beta\Delta\beta^T] = Q_\beta$. In this paper, the symbol of “ $'$ ” is the actual value.

In this article, we assume that: the position of target remain unchanged; The TDOA value are independent of GROA value, and the error are independent of each other; the positioning signal are independent of noise, the receiving noise are independent of each other from different perceptual nodes, and the positioning signal and noise are both zero mean Gaussian random process; the transmission decay coefficient of additive Gaussian noise channel is n , and there are no multipath effect and interference in the same signal transmission process.

3.2 The Construction of Positioning Equation

According to the relationship of TDOA equation $r_{i1}' = r_i' - r_1'$, we can get:

$$r_i' = r_{i1}' + r_1' \tag{7}$$

Put into formula (7) and do square operation:

$$r_{i1}'^2 + 2r_{i1}'r_1' + r_1'^2 = s_i'^T s_i' - 2s_i'^T u' + u'^T u' \tag{8}$$

Considering that $s_i' = s_i - \Delta s_i$, where r_{i1} is the measuring value of distance difference, s_i is sensor location with the error. According to the Taylor series expansion relationship, we can get:

$$r_1' = \left\| u' - s_1' \right\| \approx \left\| u' - s_1 \right\| + \rho_{u',s_1}^T \Delta s_1 \tag{9}$$

Where $\rho_{u',s_1} = (u' - s_1) / \left\| u' - s_1 \right\|$, $\hat{r}_1' = \left\| u' - s_1 \right\|$.

In the same way, considering that $s_1' = s_1 - \Delta s_1$, it can be derived according to the relationship of Taylor series expansion:

$$r_1'^2 = \left\| u' - s_1' \right\|^2 \approx \left\| u' - s_1 \right\|^2 + 2\left\| u' - s_1 \right\| \rho_{u',s_1}^T \Delta s_1 \tag{10}$$

Use the error relationship $r_{i1}' = r_{i1} - n_{i1}$ and ignore the second order error term.

$$\begin{aligned} \varepsilon_{t,i} &\doteq 2r_i'\Delta r_{i1} + 2(u' - s_i)^T \Delta s_i - 2r_i' \rho_{u',s_1}^T \Delta s_1 \\ &= r_{i1}^2 - s_i^T s_i + 2s_i^T u' - u'^T u' + 2\hat{r}_1' r_{i1} + \hat{r}_1'^2 \\ i &= 2,3,\ldots M \end{aligned} \tag{11}$$

We arrange the GROA equation $g_{i1}' = r_i' / r_1'$ and put into the time difference equation $r_{i1}' = r_i' - r_1'$:

$$g_{i1}' r_1' - r_1' = r_i' - r_1' \tag{12}$$

$$\left(g_{i1}' - 1 \right) r_1' = r_{i1}' \tag{13}$$

According to formula (9), we can get:

$$\begin{aligned} \varepsilon_{g,i} &\doteq \Delta r_{i1} - \hat{r}_1' \Delta g_{i1} + \left(g_{i1} - 1 \right) \rho_{u',s_1}^T \Delta s_1 \\ &= r_{i1} - \left(g_{i1} - 1 \right) \hat{r}_1' \quad i = 2,3,\ldots M \end{aligned} \tag{14}$$

Furthermore, do square operation by using $r_1' = \left\| u' - s_1' \right\|$.

$$r_1'^2 = s_1'^T s_1' - 2s_1'^T u' + u'^T u' \tag{15}$$

Suppose that $\hat{r}_1'^2 = \|u' - s_1\|^2$, combine formula (15) with (10), we can get the solution as follows:

$$\begin{aligned}\varepsilon_{r1} &= 2\left[(u'-s_1)^T - \hat{r}_1' \rho_{u',s_1}^T\right]\Delta s_1 \\ &= \hat{r}_1'^2 - s_1^T s_1 + 2 s_1^T u' - u'^T u'\end{aligned} \quad \textbf{(16)}$$

First, we use $u'^T u' = (a+h)^2$ instead of $u'^T P u' = \left(N+h\right)^2$ for constraint solving. Further, introduce the intermediate variable $\varphi_1' = \left[u'^T \quad \hat{r}_1' \quad \hat{r}_1'^2\right]^T$, where $\varepsilon_t = [\varepsilon_{t,2}, \varepsilon_{t,3}, \ldots, \varepsilon_{t,M}]^T$. We can get:

$$\varepsilon_{\mathbf{t}} = h_{\mathbf{t}} - G_{\mathbf{t}} \varphi_1' \quad \textbf{(17)}$$

$$h_{\mathbf{t}} = \begin{bmatrix} r_{21}^2 - s_2^T s_2 - (a+h)^2 \\ r_{31}^2 - s_3^T s_3 - (a+h)^2 \\ \vdots \\ r_{M1}^2 - s_M^T s_M - (a+h)^2 \end{bmatrix}, \ G_{\mathbf{t}} = -2\begin{bmatrix} s_2^T & r_{21} & 1/2 \\ s_3^T & r_{31} & 1/2 \\ \vdots & \vdots & \vdots \\ s_M^T & r_{M1} & 1/2 \end{bmatrix} \quad \textbf{(18)}$$

According to the error relationship, there can be derived:

$$\varepsilon_{\mathbf{t}} = B_{11}\Delta r + C_{11}\Delta g + D_{11}\Delta\beta \quad \textbf{(19)}$$

$$B_{11} = 2\begin{bmatrix} r_2' & 0 & \cdots & 0 \\ 0 & r_3' & \cdots & 0 \\ 0 & 0 & \cdots & 0 \\ 0 & 0 & \cdots & r_2' \end{bmatrix}, \ C_{11} = O_{(M-1)\times(M-1)} \quad \textbf{(20)}$$

$$D_{11} = 2\begin{bmatrix} -r_2'\rho_{u',s_1}^T & (u'-s_2)^T & 0^T & \cdots & 0^T \\ -r_3'\rho_{u',s_1}^T & 0^T & (u'-s_3)^T & \cdots & 0^T \\ & & \cdots\cdots & & \\ r_M'\rho_{u',s_1}^T & 0^T & 0^T & \cdots & (u'-s_M)^T \end{bmatrix} \quad \textbf{(21)}$$

Where 0 is the zero vector of 3×1 dimensions.
In the same way, $\varepsilon_g = [\varepsilon_{g,2}, \varepsilon_{g,3}, \ldots, \varepsilon_{g,M}]^T$.

$$\varepsilon_{\mathbf{g}} = h_{\mathbf{g}} - G_{\mathbf{g}} \varphi_1' \quad \textbf{(22)}$$

Where:

$$h_{\mathbf{g}} = \begin{bmatrix} r_{21} \\ r_{31} \\ \vdots \\ r_{M1} \end{bmatrix}, G_{\mathbf{g}} = \begin{bmatrix} 0^T & g_{21}-1 & 0 \\ 0^T & g_{31}-1 & 0 \\ \vdots & \vdots & \vdots \\ 0^T & g_{M1}-1 & 0 \end{bmatrix} \quad \textbf{(23)}$$

We can get the following equation according to the error relationship.

$$\varepsilon_g = B_{12}\Delta r + C_{12}\Delta g + D_{12}\Delta\beta \quad \textbf{(24)}$$

$$B_{12} = I_{(M-1)\times(M-1)}, \ C_{12} = -\hat{r}_1' I_{(M-1)\times(M-1)} \quad \textbf{(25)}$$

$$D_{12}=\begin{bmatrix}(g_{21}-1)\rho_{u',s_1}^T & 0^T & 0^T & \cdots & 0^T\\ (g_{31}-1)\rho_{u',s_1}^T & 0^T & 0^T & \cdots & 0^T\\ \cdots & \cdots & \cdots & \cdots & \cdots\\ (g_{M1}-1)\rho_{u',s_1}^T & 0^T & 0^T & \cdots & 0^T\end{bmatrix} \tag{26}$$

Where $I_{(M-1)\times(M-1)}$ is the $M-1$ unit matrix and 0 is the 3×1 dimensions zero vector.

As for formula (16):

$$\begin{aligned}\varepsilon_r=\varepsilon_{r1}&=h_r-G_r\varphi_1'\\&=B_{13}\Delta r+C_{13}\Delta g+D_{13}\Delta\beta\end{aligned} \tag{27}$$

$$h_{\mathbf{r}}=-s_1^Ts_1-(a+h)^2,\ G_{\mathbf{r}}=\left[-2s_1^T,0,-1\right] \tag{28}$$

$$\begin{aligned}&B_{13}=0_{(M-1)\times1}^T, C_{13}=0_{(M-1)\times1}^T,\\&D_{13}=2\left[(u'-s_1)^T-\hat{r}_1^o\rho_{u',s_1}^T \quad 0^T \quad \cdots \quad 0^T\right]\end{aligned} \tag{29}$$

Furthermore, $\varepsilon_1=[\varepsilon_t^T,\varepsilon_g^T,\varepsilon_r]^T$ is the measuring vector.

$$\varepsilon_1=h_1-G_1\varphi_1' \tag{30}$$

Where $h_1=[h_t^T,h_g^T,h_r]^T$, $G_1=[G_t^T,G_g^T,G_r^T]^T$. The formula (27) is the nonlinear equation. If u' has nothing to do with $\hat{r}_1'$ and $\hat{r}_1'^2$, we change formula (27) be the linear equation about φ_1'. By the weighted least squares principle, we can get:

$$\varphi_1=\left(G_1^TW_1G_1\right)^{-1}G_1^TW_1h_1 \tag{31}$$

Where W_1 is the weighted matrix.

$$W_1=E\left[\varepsilon_1\varepsilon_1^T\right]^{-1} \tag{32}$$

We also know that:

$$\varepsilon_1=B_1\Delta r+C_1\Delta g+D_1\Delta\beta \tag{33}$$

$$B_1=\begin{bmatrix}B_{11}\\B_{12}\\B_{13}\end{bmatrix},C_1=\begin{bmatrix}C_{11}\\C_{12}\\C_{13}\end{bmatrix},D_1=\begin{bmatrix}D_{11}\\D_{12}\\D_{13}\end{bmatrix} \tag{34}$$

So we can derive the solution:

$$W_1=\left(B_1Q_rB_1^T+C_1Q_gC_1^T+D_1Q_\beta D_1^T\right)^{-1} \tag{35}$$

The estimation error is:

$$\Delta\varphi_1=\varphi_1-\varphi_1'=\left(G_1^TW_1G_1\right)^{-1}G_1^TW_1\varepsilon_1 \tag{36}$$

The estimation error covariance matrix is:

$$\operatorname{cov}(\varphi_1)=\left(G_1^TW_1G_1\right)^{-1} \tag{37}$$

3.3 Positioning Results Optimization

To reduce the positioning error and ensure the accurate coordinate, we should select the suitable parameters with adopting the appropriate optimization algorithm. In the first step, this article proposes the glowworm optimization algorithm based on the flight mechanism to optimize formula (37). The theory is introducing the random Levy flight mechanism to adjust the particle trajectory based on the glowworm algorithm. It not only helps to get out of the local optimum, but also can get better convergence when the particles are in the global optimum. Its main function is that when the particles move in a small range near the local optimum, the jump of a large step can be given out.

Flight Levy mechanism is proposed by French mathematician Paul Pierre Levy. It is a kind of Markov chain, which characterizes the step size that should meet the Levy condition. n is the dimension of the solution, and the gamma function is Γ, β is step size.

$$\sigma = (\Gamma(1+\beta) * sin(3.14 * \beta / 2) / (\Gamma((1+\beta)/2) * \beta * 2^{((\beta - 1)/2))})^{(1/\beta)}; \quad \textbf{(38)}$$

$$\begin{aligned} u &= rand(n,1) * \sigma; \\ v &= rand(n,1); \\ a &= \alpha * (u / abs(v)^{1/\beta}); \end{aligned} \quad \textbf{(39)}$$

Many animals in the nature want to search for food in the uncertain environment. The ideal way is to use Levy flight search strategy, in this form of search, short distance carpet of cable and the occasional long distance raid. Short distance carpet cable can ensure that animals in the foraging process carefully search its surroundings in a small range. The distance to foraging are closer and easy to quickly find the target; and occasionally raid of long distance and ensure its to enter another region and in the wider range search, is far from the target distance can quickly reach the location of the target small area. In view of the advantages of Levy flight, many scholars have been inspired by it. In the evolutionary strategy, the Levy flight strategy is introduced, and the performance of the improved algorithm is improved.

Based on Levy flight mechanism, in the space of d dimension, the formula for the position of the particle at the time of the improved X is updated at t:

$$x_i(t+1) = x_i(t) + s * (x_j(t) - x_i(t)) / \| x_j(t) - x_i(t) \| + \alpha * sign(rand - 0.5) \oplus levy(\lambda) \quad \textbf{(40)}$$

The GSO algorithm mainly includes the initialization of the glowworm, the update of the fluorescence, the update of the position and the function of decision making. For the initialization of the glowworm groups, to set each individual carried the same Lucifer in concentration L_0 and sensing radius R_0. The i glowworms in the T iterations of the position for $X_i(T)$, which corresponds to the objective function value of $L_i(T)$, a Lucifer in update equations for $f(X_i(T))$ conversion for the individual carries the fluorescent values:

$$L_i(t) = (1-\rho) * L_i(t-1) + r * F(x_i(t)) \quad \textbf{(41)}$$

Each individual in its dynamic decision making domain radius $R_{id}(t)$, the individual with a higher value of $N_i(t) = \{ j : d_{ij}(t) < R_{id}(t); L_i(t) < L_j(t) \}$, where $0 < R_{id} < R_s$, R_s is the individual's perception radius. The probability $P_{ij}(t)$ of the individual $N_i(t)$ within the j is selected, and the probability equation is:

$$P_{ij}(t) = (L_j(t) - L_i(t)) / (\sum_{k \in N_i(t)} L_k(t) - L_i(t)) \quad \textbf{(42)}$$

Position updating equation:

$$x_i(t+1) = x_i(t) + s * (x_j(t) - x_i(t)) / \| x_j(t) - x_i(t) \| \quad \textbf{(43)}$$

Where s is a moving step, the general value of s=0.03.

Dynamic decision radius update domain is:

$$R_d^i(t+1) = \min\{R_s, \max\{0, R_d^i(t) + \beta * (n_t - abs(N_i(t)))\}\} \quad \textbf{(44)}$$

The specific steps of the GSO algorithm with the flight theory (Levy-GSO) are as follows:

(1) The size of the firefly population is n, the size of the L_0 is m, the radius of the firefly was R_0, the number of iterations is t, the number of iterations is R_s, the number of iterations is t, the volatile coefficient for fluorescein is μ, the update rate of fluorescein is κ;

(2) According to the formula (41) equation, the size of the fluorescein carried by each firefly is set;

(3) In the $R_{id}(t)$ of its dynamic decision making range, each individual is composed of $N_i(t) = \left\{j : d_{ij}(t) < R_{id}(t); L_i(t) < L_j(t)\right\}$, where $0 < R_{id} \leq R_s$, R_s is the individual perception radius;

(4) According to formula (42) the probability $P_{ij}(t)$ for calculation of the i of the firefly j to its collection neighborhood;

(5) Randomly selected individual j from the best individual;

(6) The position is updated according to formula (43);

(7) In accordance with formula (44) a decision to update the scope of the role of the radius;

(8) When the number of iterations is not reached the maximum number of iterations, the return (2) continues to execute until the end of the iteration till the output results are given.

3.4 The Steps of the Algorithm

To summarize, the steps of TDOA and GROA algorithm based on the Levy-GSO (LGSO - TDOA) as follows:

The definition of weight matrix W_1 as formula (35), φ_1' is the intermediate variable according to formula (30), so we can solve φ_1. In the actual, we get the initial solution u_0 of target location. Finally, we get the initial convergence estimate u of target position after repeat the first step.

We solve the target location formula (39) by Levy-GSO algorithm steps until it reaches the maximum number of iterations, then we get the more accurate target location.

4 Simulation Results

In order to have the speed of optimization and quality of the settlement at the same time, we should select the appropriate population size and the number of iteration according to the actual size of environment. Meanwhile, we make the particles produced adaptive mutation at a certain probability to avoid the Levy-GSO algorithm in the optimization process. The iterative curve is shown in Fig. 2, we use the maximum iterations number for 300 in this paper.

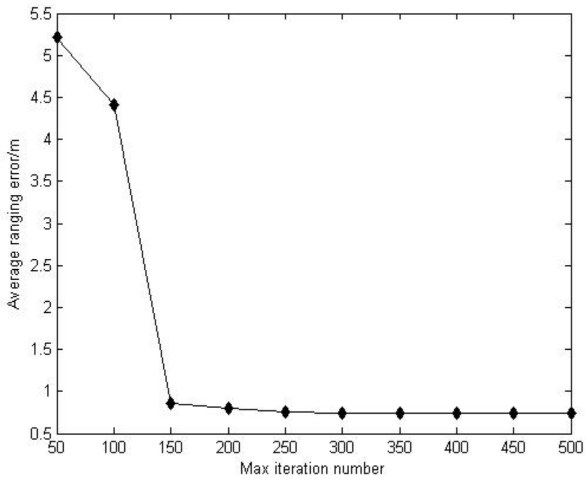

Fig. 2. The iterative curve of Levy-GSO

Under the conditions of existing error, RDOA, GROA and receiving sensor location are generated by adding the covariance matrix $Q_{\mathbf{r}} = \sigma_{\mathbf{r}}^2 R$, $Q_g = \sigma_g^2 R$ and $Q_\beta = \sigma_s^2 R$. R is σ_r^2 dimension matrix, which the diagonal elements are 1 and the rest elements are 0.5. And σ_r^2 , σ_g^2 , σ_s^2 are error power of RDOA, GROA value and receiving sensor location respectively.

In order to verify the feasibility, as well as the robustness when appears environmental fluctuation, this paper uses the MATLAB tool to do simulation experiments. We mainly test the impact of following parameters on the performance of this algorithm: (1) The ranging error; (2) The number of reference nodes and Gaussian random variable variance; (3) The root mean square error (RMSE). And compare the improved localization mechanism with the TDOA algorithm in aspects of experiment cost and energy consumption.

4.1 The Ranging Error

With the increase of ranging error, the proposed LGSO-TDOA algorithm in this paper and TDOA algorithm both have the increase trend. As shown in Fig. 3, the positioning error growth rate of LGSO-TDOA algorithm is relative low.

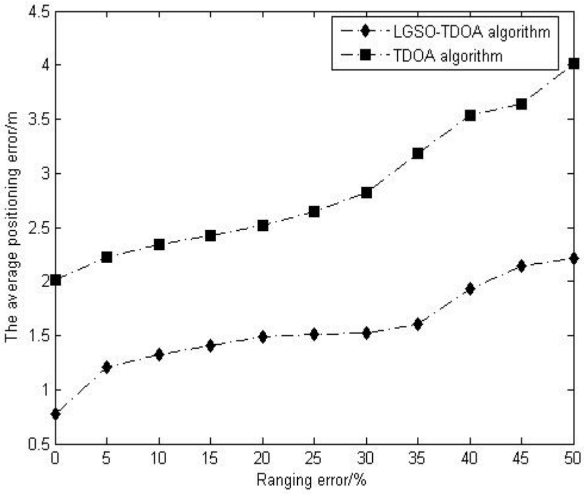

Fig. 3. The impact of ranging error on the average positioning error

Table 1. Comparison of the two algorithms error

Experimental data	LGSO-TDOA algorithm	TDOA algorithm
The average	1.571	2.832
The maximum error	2.211	3.911
The minimum error	0.886	2.013

From the above, the maximum and minimum error of LGSO-TDOA algorithm has decreased to 2.211 and 0.886 respectively compared with TDOA algorithm. And the average decreases by 45%, which proves the LGSO-TDOA algorithm has the better robustness to the effect of the ranging error.

4.2 The Number of Reference Nodes and Gaussian Random Variable Variance

Fig. 2 to Fig. 4 shows the cumulative density functions of LGSO-TDOA algorithm. We deploy $n = 2$ and $n = 4$ reference node respectively environment to test LGSO-TDOA performance under different number of nodes. Considering different Gaussian variance at the same time, we verify the positioning error distribution. Fig. 4 to Fig. 6 show Gaussian random variable variance σ^2 = 2, 4, 8.

We can find from the above tables, the two curves in the Fig. 4 to Fig. 6 is very close, which suggests that LGSO-TDOA algorithm could maintain higher performance under the less reference nodes condition. As for the problem of Gaussian random variables interference, we can know that LGSO-TDOA algorithm provides precise and stable positioning results from the Fig. 6.

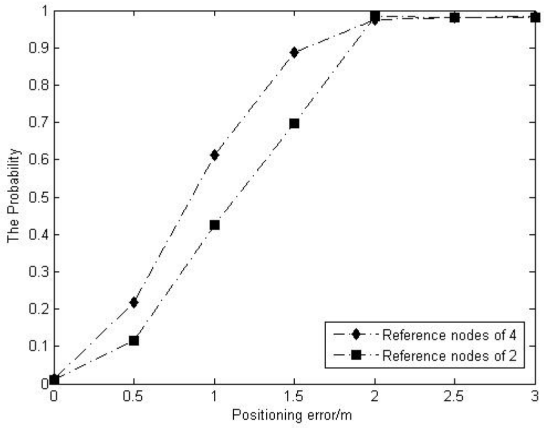

Fig. 4. Localization error cumulative density functions achieved with LGSO-TDOA algorithm for $\sigma^2 = 2$

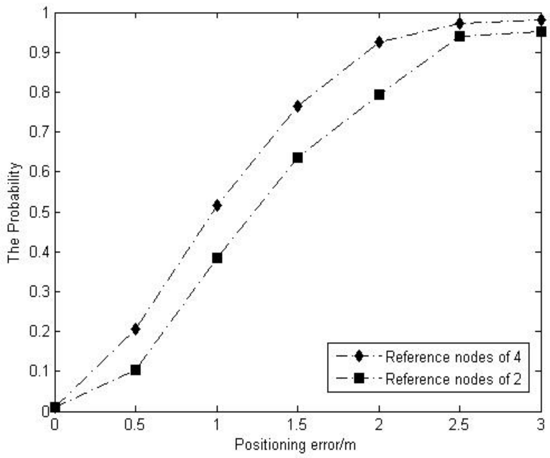

Fig. 5. Localization error cumulative density functions achieved with LGSO-TDOA algorithm for $\sigma^2 = 4$

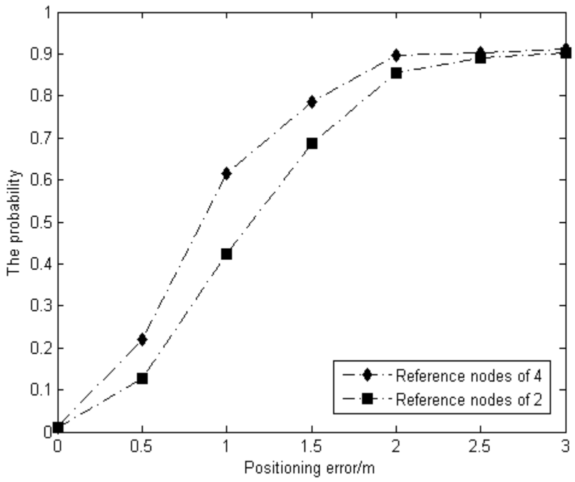

Fig. 6. Localization error cumulative density functions achieved with LGSO-TDOA algorithm for $\sigma^2 = 8$

4.3 The Error of Root Mean Square

$R\mathrm{MSE}(u) = \left(\sum_{l=1}^{L} \left\| u^{(l)} - u' \right\|^2 \Big/ L \right)^{1/2}$, where $u^{(l)}$ is the target location estimate value, u' is the actual location, σ_t=5000 is the independent simulation running times. Supposing that σ_t is the mean root of time difference measuring error and require $\sigma_r = c \bullet \sigma_t$. In Fig. 7, $\sigma_g = -20dB$, $\sigma_s = -40dB$. In Fig. 8, $\sigma_t = -60dB$, $\sigma_s = -20dB$. In Fig. 9, $\sigma_t = -60dB$, $\sigma_g = -20dB$.

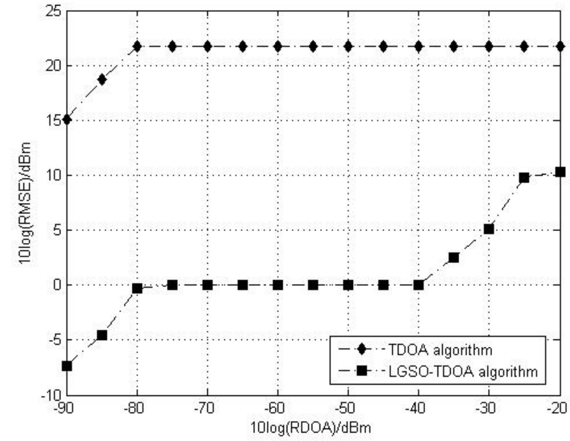

Fig. 7. Positioning error under different time measurement

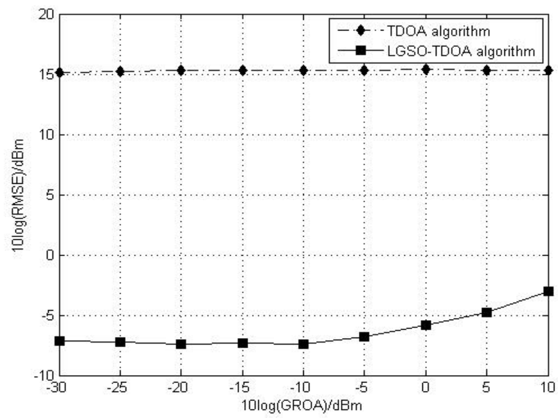

Fig. 8. Positioning error under different amplitude ratio

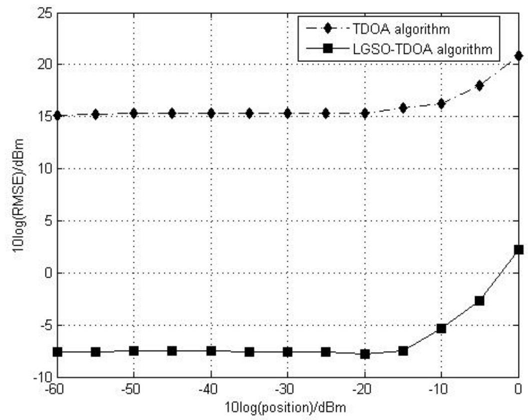

Fig. 9. Positioning error under different receiving sensor location

In Fig. 7 to Fig. 9, we can find that: (1) Under the same condition of parameter error, the LGSO-TDOA location model can be improved about 23dB compared with TDOA model. (2) The positioning accuracy is mainly decided by the smaller parameter of TDOA and GROA measurement error. The another parameter has the small influence on the localization result; (3) The root mean square error of LGSO-TDOA algorithm is near -7 dBm and the fluctuation keeps unchanged.

4.4 Energy Consumption and Experiment Cost

Fig. 10 is the experiment cost simulation of LGSO-TDOA and TDOA algorithm. As is shown, when under the situation of less nodes, two algorithms of experiment cost are similar. But LGSO-TDOA algorithm increase trend is very gentle and significantly lower than the TDOA algorithm with increasing number of nodes, namely LGSO-TDOA algorithm has the lower cost than TDOA algorithm.

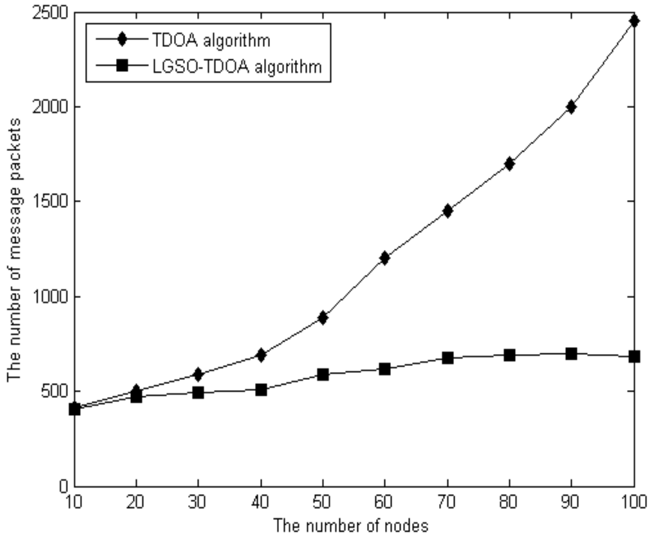

Fig. 10. The analysis of algorithm cost

Fig. 11 shows the energy consumption of two algorithms under different number of nodes. The figure shows that the energy consumption of the two algorithms is on the rise with the increase of the number of nodes. The LGSO-TDOA energy consumption has the very big improvement compared to TDOA algorithm. When under the same positioning accuracy, LGSO-TDOA algorithm is better than TDOA algorithm to extend the service life of the node.

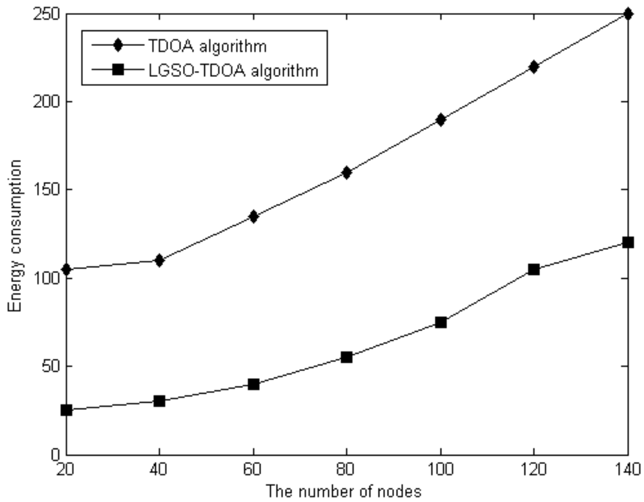

Fig. 11. The analysis of algorithm energy consumption

5 Conclusions

This paper presented an adaptive TDOA and GROA localization based on Levy-GSO algorithm. We develop the correction two-step weighted least-squares method to solve the problem of the nonlinear relationship between localization equation and the target location. And we propose the glowworm swarm optimization based on Levy mechanism to find the optimal localization quickly and accurately. The simulation results demonstrated that our proposed algorithm has a better performance in terms of localization accuracy than the original TDOA method, especially the limited reference nodes and poor capacity of resisting disturbance. Therefore, LGSO-TDOA algorithm is an efficient algorithm and it is more suitable for sensor networks of dense nodes and large scale compared with other improved TDOA algorithms. However, this paper is only compared with algorithm based on the TDOA under different number of reference nodes and ranging error, which does not consider the other parameters affection. And the experiments are under the ideal situation, ignoring interferences of external environmental factors. In the future, we plan to overcome the above disadvantages and explore the other improvements and incorporate them into the LGSO-TDOA algorithm.

Acknowledgements

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