Research on the Application of Improved Salp Swarm Algorithm in Time Difference of Arrival of Passive Location

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***Abstract*—According to the shortcomings of slow positioning speed and low detection accuracy of passive positioning that uses time difference of arrival (TDOA), an innovative location model of extreme learning machine (ELM) which is improved by Salp Swarm Algorithm (SSA) in view of Logistic Mapping, Opposition-Based Learning and Cauchy Mutation (LOCSSA) is put forward. The method firstly initializes the population by Logistic mapping and improves SSA by Opposition Based Learning and Cauchy mutation. Then uses LOCSSA to look for the optimal weights and biases of ELM. Finally, LOCSSA is used to locate the target. The results show that the ELM positioning model of LOCSSA has better accuracy and stability for target positioning, which demonstrate that the method is feasible.**

Keywords- time difference of arrival; salp swarm algorithm; extreme learning machine; Cauchy mutation

I. INTRODUCTION

Passive positioning means that the observation station does not transmit radio signals to the detection target, but uses the electromagnetic wave signals radiated, forwarded and reflected by the target to locate the target. Because of its good concealment, strong survivability, long operating distance, strong anti-interference ability, it is widely used in the field of electronic reconnaissance. According to the different parameters of target measurement information, there are also many types of passive positioning systems, for example direction of arrival positioning (DOA), time of arrival positioning (TOA), and time difference of arrival positioning (TDOA). Among them, TDOA has a wide range of applications and research widely due to its advantages of high positioning accuracy, fast speed, low system complexity and low hardware requirements.

Currently, domestic and foreign scholars are doing a lot of research on the TDOA problem. Common traditional algorithms include Taylor-series estimation method [1], constrained overall least squares method [2], Spherical Interpolation (SI) [3], Approximate Maximum Likelihood (AML) [4], such algorithms have poor positioning ability, poor convergence, and high requirements for reconnaissance stations. In addition to the above-mentioned traditional algorithms, some researchers apply intelligent optimization algorithms to the TDOA problem. In 2006, Li J F et al. [5] put forward to employ Particle Swarm 0ptimization (PSO) to solve the problem of TDOA. Maja et al. [6] applied an Improved Genetic Algorithm (IGA) for TDOA positioning in 2016. In 2022, Chen G W et al. [7] led Whale Optimization Algorithm (WOA) into TDOA localization. The intelligent algorithm omits complex calculation formulas, generates lots of random points in the range during initialization, and finds the optimal solution in the random points through iteration. This type of approach conquers the disadvantage of least squares method requiring multiple observation stations. In 2018, Song P et al. [8] gave an improved dragonfly algorithm (LACMODA). LACMODA was made use of looking for the optimal weights and biases of the ELM. Through the improved ELM, TDOA and the target latitude and longitude learning realizes the target position prediction. Compared with the traditional algorithm, although the accuracy has been greatly improved, the dragonfly algorithm has poor optimization accuracy and takes a long time, so there is still a large room for improvement.

In 2017, Mirjalili et al. [9] proposed the salp swarm algorithm (SSA). The algorithm originated from the group behavior of salps in the deep sea. Through leading, following and other processes, an efficient optimization scheme was constructed. SSA has a simple optimization mechanism, few parameter settings, and has a strong global search capability. In this paper, LOCSSA is compared with other intelligent algorithms, LOCSSA is applied to the extreme learning machine parameter search, and the improved ELM is used to predict the target position to further improve the detection accuracy.

II. THE PRINCIPLE AND METHOD OF TDOA

A. The principle of multi-station passive positioning of TDOA

A multi-station passive positioning of TDOA system usually consists of a master station and several auxiliary stations. The system receives the electromagnetic signal from the same air target, and uses the time difference between each auxiliary station and the main station to locate the target. As shown in Figure 1. As shown in Fig. 1.

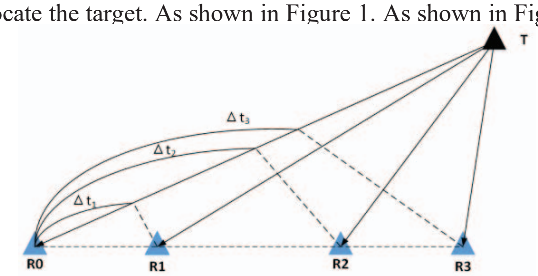

Figure 1. Diagram of multi-station passive positioning of TDOA

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In Fig. 1, T is the radiation source target, R_0 is the master station, R_1, R_2, R_3 is the auxiliary station, $\Delta t_i\left(i=1,2,3\right)$ is the time difference between the time of arriving at the master station and the time of arriving at the auxiliary stations. The positioning principle takes the sensor nodes corresponding to the auxiliary station and the main station as the focus, and uses the distance difference corresponding to each time difference as a fixed value to form multiple sets of hyperbolas. By solving the multiple sets of hyperbolic equations, the estimated target position can be obtained. For the specific model, please refer to the introduction of Wang Y C et al. [10].

B. TDOA localization model based on ELM

In 2004, Huang et al. [11] raised the extreme learning machine (ELM). It is a forward neural network that has single hidden layer. It determines the output weight by randomly selecting the weight of the neural network. Compared with traditional neural networks (such as BP neural network), ELM not only has a very fast learning rate, but also has good generalization performance, so it is widely used in various prediction models.

Song Ping et al. [9] used the TDOA information of each sub-receiving station and transmitting station in the multi-base station joint positioning system as the ELM input parameter to fit the prediction of the detected target position in the detection area. The TDOA information of each receiving station is used as the input layer parameter of ELM in the passive positioning model of ELM. Scanning and detecting the target area, it is assumed that the time of the target transmission signal received by the main receiving station is t_0, and the time of receiving the target transmission signal received by each sub-receiving station is t_1, t_2, t_3, so the input vector $\mathbf{V}$ of the ELM input layer represents as follows:

$$\mathbf{V}=\left(\nabla \mathrm{t}_{10}, \nabla t_{20}, \nabla t_{30}\right), \tag{1}$$

In (1): ∇t_{i0} represents the difference between the time t_i when the receiving station i receives the target echo and the time t_0 when the main receiving station R_0 receives the target echo, $i=1,2,3$.

The latitude and longitude of the detected target is used as the output vector of ELM. The ELM output vector $\mathbf{O}$ can be expressed as:

$$\mathbf{O}=\left(B_{\mathrm{A}}, L_{\mathrm{A}}\right), \tag{2}$$

In (2): B_{A} represents latitude, L_{A} represents longitude.

III. Improved SSA to Optimize the Localization Model of ELM

A. Improvement of SSA

1) Logistic mapping initialization population

Logistic mapping [12] is a one-dimensional chaotic map that is widely used and has a very simple form, and its formula is Eq. (3):

$$z_{i+1}=\mu z_i(1-z_i), \tag{3}$$

in (3), $i=0,1,2,\cdots$, μ are the control parameters, $\mu\in\left(0,4\right]$, $z_i\in\left[0,1\right]$. When $\mu=4$, it shows typical chaotic characteristics. Population initialization affects greatly on the convergence speed and optimization performance of SSA. Logistic mapping is used to initialize the salp population in this paper.

2) Opposition Based Learning

The substance of Opposition Based Learning (OBL) [13] means that the current solution and the reverse solution are searched at the same time in the process of finding the optimal solution, and the better solution is used as the problem solution. It can expand the search scope and improve the search efficiency of the algorithm. The leader only updates its position under the guidance of the food source. Due to the lack of prior knowledge, it is difficult to determine whether the current food source is in the global optimum. If the food source is in the local optimum, the entire salps chain group will gather in the local optimum area, and the population diversity will be lost, which will cause the algorithm to converge to the local optimum. Therefore, OBL can enhance the ability to flee local optimum of SSA. The description of generating the inverse solution of individual salps using OBL is as follows:

$X_i^t=\left[X_{i,1}^t, X_{i,2}^t, \cdots, X_{i,N}^t\right]$ is a feasible solution of the t generation of the problem, $X_{i,j}^t$ is the position of the i individual in the j dimension, and $X_{i,j}^{t\ '}$ is the inverse solution corresponding to $X_{i,j}^t$. The formula is expressed as follows:

$$X_{i,j}^{t\ '}=c\_ub_j+c\_lb_j-X_{i,j}^t, \tag{4}$$

in (4): c_ub_j and c_lb_j are respectively the upper and lower limits of the j dimension of the individual at the current iteration t, $i\in\left[1,D\right]$, D is the amount of individuals, $j\in\left[1,N\right]$, N is the space dimension of the feasible solution.

$$P_s=\exp\left(\left(1-\frac{l}{Max\_iter}\right)^{20}\right), \tag{5}$$

in (5), l is the current number of iterations, and Max_iter is the total number of iterations.

Calculate the value of P_s according to (5), P_s compare with the size of the random number, if the random number is better than P_s, perform OBL to renew the individual position, otherwise keep the individual position.

3) Cauchy Mutation

The Cauchy mutation operator is introduced to the optimal individual in SSA, and new individuals are produced through the mutation operation to expand the population search scope. After the mutation operation, the new individual can effectively lead other individuals to flee the local optimum. Cauchy mutation can avoid getting into local optimum. Using the standard Cauchy distribution for mutation processing can help individuals after mutation jump out of local extreme values quickly. According to (6), the current optimal individual is mutated:

$$F_{new}^{t} = F^{t} + F^{t} * Cauchy(0,1), \quad (6)$$

in (6): F^{t} is the position of the food in the t generation, F_{new}^{t} and is the position after mixed mutation.

The solution generated by the Cauchy mutation is accepted or not by the Metropolis criterion [14].

$$P_m = \begin{cases} 1, & f_{\text{new}} \leq f_{\text{g}} \\ \exp\left(-\left(f_{\text{new}} - f_{\text{g}}\right)/T_e\right), & \text{otherwise} \end{cases}, \quad (7)$$

in (7): T_e is the current temperature, and f_{new} represents the solution after mutation.

Obtain the fitness value of the new and old food source positions after the perturbation mutation update is performed on the food source position, and use (7) to calculate P_m through the fitness value. Compare the size of P_m and the random number, if the random number is better than P_m, give up the position of the new food source, otherwise accept the position of the new food source. The algorithm selects the optimal value while preserving the potential foraging position.

B. LOCSSA-ELM target localization model

Huang G B et al. [11] proposed an extreme learning machine (ELM). The sample can be obtained by a least square method to obtain a better output weight without secondary adjustment, and the entire training of the network is completed. However, there is still room for further optimization of the prediction accuracy of ELM, and intelligent algorithms can be applied to search the optimal weights and biases of ELM to make the results better.

Compared with SSA, LOCSSA has a better optimization effect. LOCSSA is used to find the optimal input weights and hidden layer biases of the ELM, and the optimized ELM network is applied to the target positioning to realize the optimization. The positioning of the target can reach better positioning accuracy. The steps of LOCSSA-ELM are shown in Fig. 2:

In addition, for estimating the optimization performance of the algorithm, (8) is applied here for the fitness evaluation function:

$$f = m \times \left(\sum_{i=1}^{M} \left| P_i^{*} - P_i \right| \right), \quad (8)$$

in (8): M represents the total number of input training data, P_i^{*} is the position predicted by the model for the input target, P_i is the actual input target position, and m is a non-zero constant.

IV. SIMULATION EXPERIMENT AND ANALYSIS

A. Comparative analysis of algorithm performance results

1) Test function selection

For measuring the result of LOCSSA, seven benchmark functions [15] are selected here, and the information is shown in Table Ⅰ.

2) Algorithm comparison

This paper selects three relatively new swarm intelligence optimization algorithms—Dragonfly algorithm (DA) [16], Grey Wolf algorithm (GWO) [17], Salp Swarm algorithm (SSA) [9] and LOCSSA for comparison, and the population number of the above four algorithms is assigned to 10, the dimension of the problem is assigned to 30, the number of iterations of the algorithm is assigned to 300, the basic parameters of the four algorithms are the same, and 30 optimization experiments are carried out for each function. The simulation results are shown in Table Ⅱ. Compared with other functions, LOCSSA is closer to the optimal value in the field of mean and variance, indicating that LOCSSA has good optimization results and high stability. Compared with the SSA, LOCSSA has higher accuracy in solving the problem as a whole, and it is difficult to get into the local optimal solution of the problem.

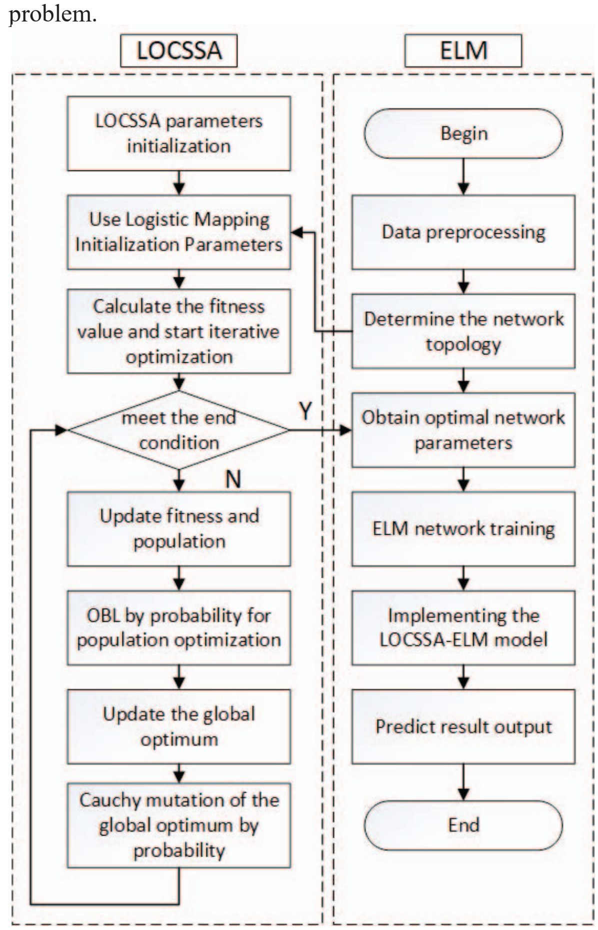

Figure 2. LOCSSA-ELM flow chart

TABLE I. BENCHMARK FUNCTIONS

Function	Function name	Dimension	Search range	Optimal value
f_1	Sphere	30	[-100,100]	0
f_2	Schwefel 2.22	30	[-10,10]	0
f_3	Schwefel 2.21	30	[-100,100]	0
f_4	Rosenbrock	30	[-30,30]	0
f_5	Rastrigin	30	[-5.12,5.12]	0
f_6	Penalized 1	30	[-50,50]	0
f_7	Ackley	30	[-32,32]	0

TABLE II. OPTIMIZATION RESULTS OF LOCSSA

function		DA	GWO	SSA	LOCSSA
f_1	Mean	7.51E+03	1.01E-07	6.11E+02	**7.29E-37**
	Std	3.27E+03	9.27E-08	2.70E+02	**3.99E-36**
f_2	Mean	4.81E+01	1.60E-05	5.75E+01	**8.50E-32**
	Std	2.50E+01	7.89E-06	2.66E+01	**3.63E-31**
f_3	Mean	4.30E+01	6.14E-02	3.19E+01	**1.07E-30**
	Std	1.40E+01	4.40E-02	4.91E+01	**5.60E-30**
f_4	Mean	8.40E+06	2.92E+01	1.15E+05	**2.87E+01**
	Std	1.58E+07	3.93E+00	1.35E+05	**2.44E-02**
f_5	Mean	2.35E+02	1.09E+01	1.28E+02	**0**
	Std	3.72E+01	6.97E+00	2.71E+01	**0**
f_6	Mean	7.12E+05	2.56E-01	1.50E+02	**1.25E-01**
	Std	1.49E+06	1.70E-01	2.94E+02	**7.65E-02**
f_7	Mean	7.80E+00	1.11E-09	1.81E+00	**8.88E-16**
	Std	5.07E+00	8.99E-10	1.11E+00	**8.88E-16**

B. Positioning Model Validation

For the sake of checking the validity of the research model in this paper, a master station R_0 and 3 auxiliary stations R_1, R_2, R_3 are selected to form a time difference positioning system. Among them, the longitude and latitude of each station are respectively taken as: R_0 (30.5443°N, 114.3660°E), R_1 (30.4013°N, 114.2438°E), R_2 (30.4081°N, 114.5117°E), R_3 (30.3661°N, 114.3507°E), The distance between each station is about 20km, the distance between the target and each station is 30~70km, and the time measurement accuracy of each station is $100ns$. In the experiment, 500 groups of TDOA data were collected, and the collected TDOA data were split into training set and test set in accordance with the ratio of 9:1. In the experiment, for further checking the superiority of the model in this paper, the ELM, DA-ELM, SSA-ELM and the LOCSSA-ELM model in this paper are compared. During the experiment, the normalized data collected was input into the ELM, DA-ELM, SSA-ELM and LOCSSA-ELM positioning models, the population size of the three intelligent optimization algorithms was assigned to 10, and the maximum number of iterations was assigned to 50. The search space of the solution vector is assigned to $[-1,1]$, in the LOCSSA-ELM localization model, the temperature T_e is 300.

For assessing the effect of each positioning model, the mean absolute error cc is used to evaluate the accuracy of the prediction of each model.

$$M_{AE} = \frac{1}{N_T}\sum_{1}^{N_T}\left|P_n - P_n^*\right|, \tag{9}$$

in (9): N_T is the total number of test samples. P_n^* is the position predicted by the model for the input target, and P_n is real target position. The smaller M_{AE} is, the higher the prediction accuracy of the algorithm is. Fig. 3 and Fig. 4 show the experimental results.

Fig. 3 shows the prediction of the 50 target locations in the test set by the ELM network positioning model optimized by LOCSSA. The horizontal axis is longitude and the vertical axis is latitude. It can be seen that the latitude and longitude error of the target predicted by LOCSSA-ELM and the latitude and longitude of the actual target is very small, and the position of each point is very close to the real value.

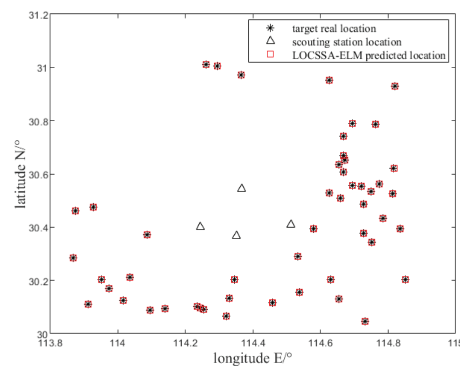

Figure 3. Target position prediction map

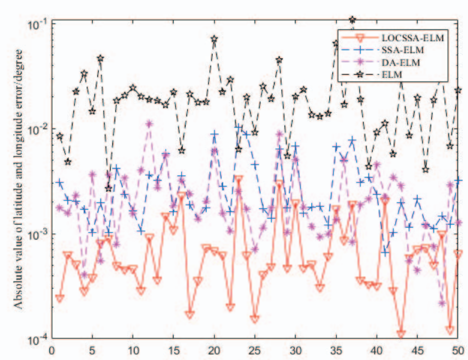

Figure 4. Longitude and latitude error of target prediction

Fig. 4 indicates the comparison chart of the target prediction latitude and longitude errors of different ELM models. The horizontal axis is the sample ordinal, and the vertical axis is M_{AE} . It can be seen that in the ELM positioning model, compared with other positioning models, the latitude and longitude errors of the LOCSSA-ELM model are relatively small as a whole.

Therefore, the LOCSSA-ELM localization model looked forward in this paper is more accurate in predicting the target position than others. It indicating that the algorithm is effective.

V. CONCLUSION

Due to the problems of poor stability and low exploration accuracy of traditional passive time difference localization algorithms, the LOCSSA-ELM localization model which optimizes ELM proposed in this paper, not only shows better global search performance when optimizing multi-dimensional problems, it has better performance and optimization speed. The ELM positioning accuracy after LOCSSA optimization is also better than that of other ELM positioning models, and has better robustness, which fully shows the effectiveness of the method in passive positioning of TDOA in this paper.

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