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A Novel Hybrid Location Algorithm Based on Chaotic Particle Swarm Optimization for Mobile Position Estimation

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ABSTRACT Location estimation is significant in mobile and ubiquitous computing systems. Considering the influence of measurement error caused by time difference of arrival (TDOA)/angle of arrival (AOA) hybrid location algorithm and the nonlinear optimization problem encountered in the location estimation, in this paper, a particle swarm optimization (PSO) algorithm based on the chaos theory is proposed for the hybrid location of mobile location estimation. Taking the TDOA/AOA hybrid location algorithm for mobile location estimation as the object, the proposed algorithm greatly improves the location performance and accuracy of mobile location estimation. First, the estimation function of the mobile station is obtained by the maximum likelihood method, and then the initial population of PSO is generated by using the estimation function of the mobile station as a fitness function. The chaotic optimized particle swarm optimization algorithm (CPSO) is used to solve the optimal solution of the optimal position of the population and obtain the optimal mobile location position estimation, which makes the TDOA/AOA location algorithm have better location performance. The simulation results have demonstrated that the performance of the proposed method compared with the traditional Chan algorithm, the Taylor algorithm, and the TDOA/AOA hybrid location algorithm, the proposed algorithm can reduce the impact of error on the location accuracy, achieve a balance of global and local search capabilities, and have a faster convergence speed and more accurate positioning accuracy.

INDEX TERMS Location algorithm, particle swarm optimization, chaos theory, time difference of arrival, arrival angle, TDOA/AOA.

I. INTRODUCTION

With the large-scale deployment of wireless networks, the rapid popularization of smart mobile terminals, the rapid development of mobile wireless communication technology and the popularization of smart phones, the location technology has been widely applied in various fields of our society [1]. In order to make personal navigation and the location information more valuable, the single-point navigation is transforming into integrated positioning services, which are widely used in industrial monitoring, management, transportation, rescue, entertainment, sports and so on. With the rapid development of mobile wireless communication technology, people's daily life is becoming more intelligent and convenient, at the same time, they also need to constantly update and improve the existing positioning technology and positioning services. Location Based service (LBS), as a basic and important service, is always providing convenience for people's lives [2]–[4]. The provision of location service cannot be separated from the support of mobile

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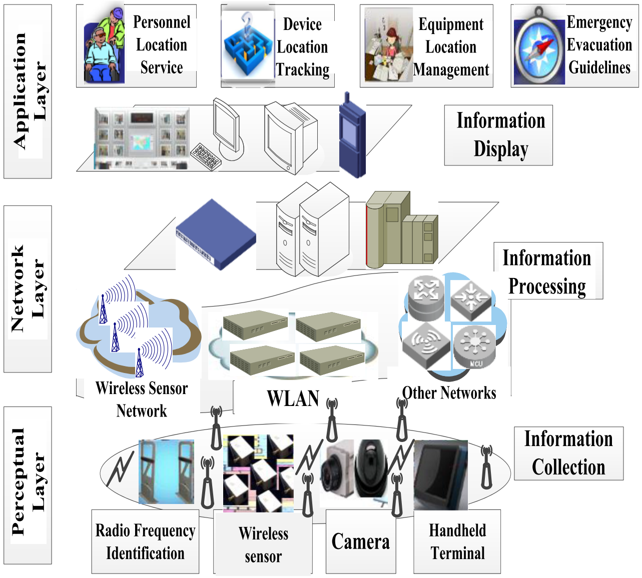

FIGURE 1. The mobile wireless positioning technology framework.

accurate positioning technology. For this reason, the various positioning technologies based on mobile terminals have received extensive attention and research. The schematic diagram of the mobile wireless positioning technology framework is shown in Figure 1. At present, the existing wireless positioning algorithm can achieve better positioning performance in the environment of signal line-of-sight (LOS) propagation. However, in a mobile environment, the non-line-of-sight (NLOS) propagation occurs when the radio waves are affected by the scattering or reflection. The non-line-of-sight propagation causes a large delay in the propagation of the radio wave, which causes the TOA and TDOA positioning methods based on the time measurement to be greatly deviated, so that the distance between the transmitter and the receiver or the corresponding distance difference cannot be correctly reflected.

A. PROBLEM STATEMENT AND MOTIVATE

In the cellular mobile communication system, due to the influence of the non-ideal propagation environment, the factors that cause the location error include the effect of non-line-of-sight (NLOS), the multipath effect, the multiple access interference and the far and near effect, except the random measurement error produced by the device measurement difference [5]. In a cellular network environment, if the path of radio wave propagation between the mobile station and the base station is blocked by the building, the radio wave can only be transmitted by non-line-of-sight propagation (NLOS) such as reflection and refraction. If the TDOA and TOA techniques are used to locate the mobile station, a positive additional over-latency delay will be generated in the TOA measurement compared to the LOS path, and an error component is also generated correspondingly in the TDOA measurement. Applying such non-Gaussian TOA or TDOA measurement with large error to the positioning estimation of the mobile station will inevitably lead to a significant degradation of the performance of the positioning algorithm, and the maximum likelihood estimation of the position of the mobile station cannot be obtained, resulting in a large deviation of the estimated position. Because of the ubiquitous spread of NLOS in urban environment, to improve the accuracy of mobile station positioning in urban environments, it is necessary to study how to identify and eliminate the effects of non-line-of-sight (NLOS). And due to the combined influence of these factors, there will be large deviations in location estimation. The wireless location research work focuses on wireless location methods based on the time-of-arrival (TOA) and angle-of-arrival (AOA) and the time difference of arrival (TDOA). These methods mainly determine the position of the mobile station by the circle, hyperbola or direction angle determined by the known location coordinates of the base station and the measured values of each time and angle. But in the mobile environment, the radio wave is affected by scattering or the reflection. The propagation of the radio wave is greatly delayed by the non-sight distance propagation, which makes the time-based measurement (TOA, TDOA) greatly deviated, which cannot correctly reflect the distance between the transmitter and the receiver or the corresponding distance. These methods reduce the adaptability and efficiency of the system. In addition, many current solutions are greatly affected by external interference errors, which also increase system overhead, resulting in waste of energy and resources. The TDOA/AOA hybrid location algorithm has more accurate localization performance than the TDOA algorithm or the AOA algorithm. TDOA is an equation for the position of MS through the arrival time difference of the electric wave. AOA is the equation of the position of the MS through the angle of arrival of the signal. How to solve the nonlinear equations composed of the two different types of nonlinear equations problem is the key and difficult point of the TDOA/AOA hybrid location algorithm [6].

B. CONTRIBUTION

In this work, we propose a chaos theory to optimize the localization algorithm of particle swarm optimization algorithm for the cellular mobile communication system. In comparison with the current general selection approaches, the main contributions of the proposed work are-

- We established the wireless communication location error model, and proved by mathematical deduction that the TDOA/AOA hybrid location problem is a complex nonlinear optimization problem.
- We proposed a wireless location method based on chaos theory optimized particle swarm optimization and apply it to TDOA/AOA hybrid location.
- Extensive numerical results are provided below which demonstrate the usage and efficiency of the proposed the TDOA/AOA hybrid location algorithm.

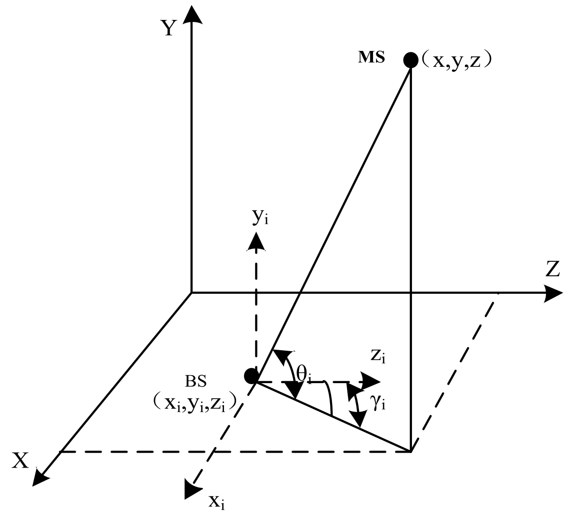

FIGURE 2. TDOA/AOA hybrid location system model.

II. RELATED WORK

In general, the TDOA/AOA hybrid location algorithm has a more accurate positioning accuracy and the measuring accuracy. Researchers have proposed various algorithms to further improve the TDOA/AOA hybrid location algorithm. Some researchers have proposed some localization algorithms based on Particle Swarm Optimization (PSO) for wireless sensor networks [7]–[9]. Meanwhile, Jia *et al.* [10] proposed a novel localization method based on the structured total least squares (STLS), in order to further reduce the estimation bias that easily arise from the traditional methods, while the RMSE of the STLS algorithm is comparable to the other methods specially when the target is outside the convex hull formed by sensors. In literature [11], the author introduced the modified polar representation to unify the localization of a source using the angle of arrival (AOA) regardless if it is near or far, utilized the hybrid bhattacharyya-barankin (HBB) bound to illustrate it is not possible to obtain the cartesian coordinates of a distant source when applying the near-field model, and proposed a preliminary solution to initialize the MLE using the semidefinite relaxation to improve the location performance. In literature [12], the author proposed a sparsity-aware hybrid target localization method in multiple-input-multiple-output (MIMO) radars from the time difference of arrival (TDOA) and angle of arrival (AOA) measurements. It is reported in [13], the author proposed the kalman filter based the hypothesis test is applied for eliminating NLOS noise which contained measurement data. The optimized solution of which the estimation error was minimized, and it can be acquired. Comprehensive the above analysis, with the increase of the error of TDOA and AOA, the final results may not be convergent.

In addition, the scholars have proposed some other methods of the node localization error. In literature [14], the author proposed a localization algorithm that uses the time difference of arrival (TDOA) and the angle of arrival (AOA) to achieve high location accuracy in three dimensions.

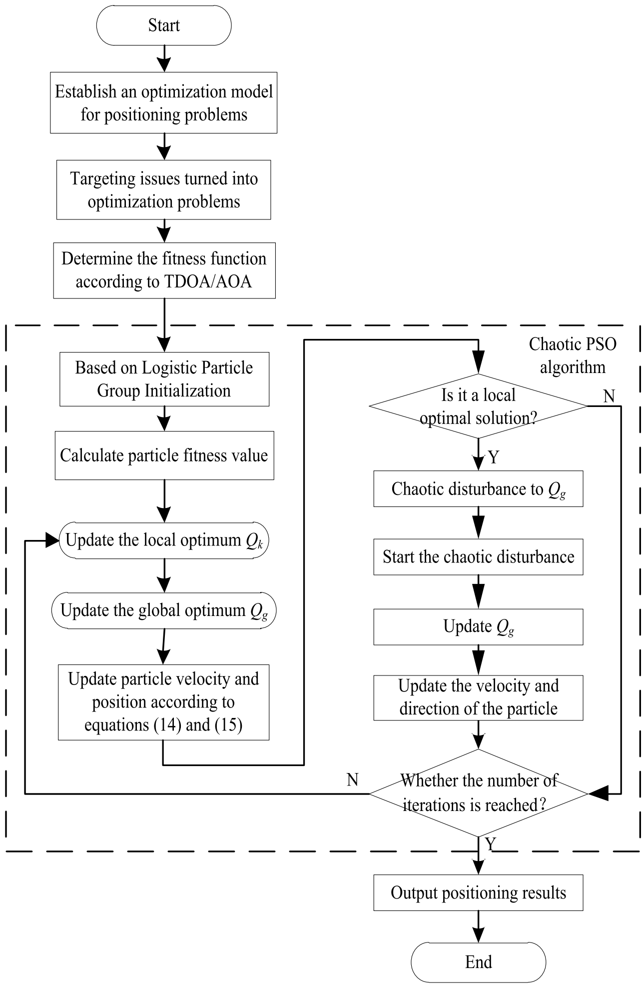

FIGURE 3. The flow chart of CPSO localization algorithm.

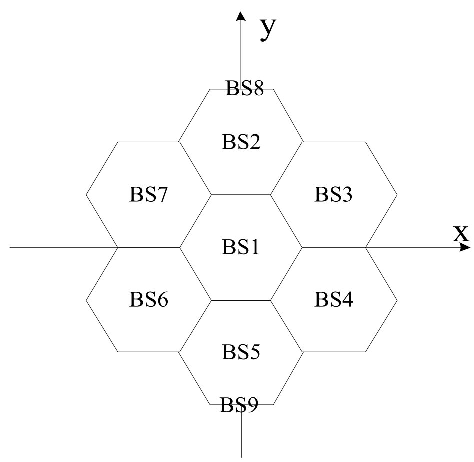

FIGURE 4. The cellular structured mobile communication system layout.

Li *et al.* [15] proposed a new closed form location algorithm for mobile user, the nonlinear TDOA and AOA measurement equations without noise were transformed to linear equations for the positions. Chang and Shen [16] addressed the model uncertainty and improve the accuracy of the estimated location under the conditions that relatively low SNR and moderate NLOS effects, a wiener estimator will be utilized to form a new efficient hybrid TOA/AOA location estimator, and the simulation results are provided to demonstrate the effectiveness of the proposed location estimation scheme. In literature [17], the author proposed the time-of-arrival (TOA) and angle-of-arrival (AOA) based random transmission directed localization (RTDL) technique, and the author depicted the capability of the proposed method to considerably reduce the localization error and effectively determine the attacker's nearest location in the network. In [18], the author presented a selective hybrid weighting approach to intra cell locate a mobile station (MS) when both the range and the angle measurements are corrupted and non-line-of-sight (NLOS) are not identified from line-of-sight (LOS) measurements.

At the same time, some scholars have carried out in-depth research on the location methods in 3 dimensional spaces. In [19], the author proposed a simple closed-form solution method by constructing new relationships between the hybrid measurements and the unknown source position for the locating passively a point source in the three-dimensional (3D) space, reduced the location error of wireless communication. In [20], the author proposed a three-dimensional (3D) passive localization method using the active time of arrival (TOA) measurement and the one TOA and two-dimensional angle of arrival (AOA) pairs observed at two stations. The proposed algorithm in this paper is the combination of TDOA and AOA method. Moreover, the equation to measure TDOA and AOA are a non-linear equation with respect to position of target.

Comprehensive the above analysis and in order to address the existing drawbacks in those methods, in this paper, a particle swarm optimization (PSO) algorithm based on the chaos theory is proposed for the hybrid location of mobile location estimation. The improved particle swarm optimization algorithm has the faster convergence speed and it can obtain the aim of optimizing. Firstly, the estimation function of mobile station is obtained by maximum likelihood method, and then the initial population of PSO is generated by using the estimation function of mobile station as fitness function. The chaotic theory optimized particle swarm optimization algorithm (CPSO) is used to solve the optimal solution of the optimal position of the population, and obtain the optimal mobile location position estimation, which makes the TDOA/AOA hybrid location algorithm have the better location performance. Finally, the simulation and comparison results show that the proposed algorithm has the superior location performance.

The remainder of this paper is organized as follows. In Section 3 we introduce the establishment of location error model. TDOA/AOA hybrid location algorithm is introduced in Section 4, In Section 5 details the implementation of Particle swarm optimization based on chaos theory. Experimental results are analyzed in Section 6, and Section 7 concludes this paper.

III. ERROR MODEL ESTABLISHMENTS

Due to the complexity of the mobile communication environment, the radio waves are mainly transmitted between the mobile phone and the base station in the form of reflection, refraction, and scattering. The signal propagation time is longer than the line-of-sight propagation time under the ideal conditions [21]. It is the additional delay τ caused by the non-line-of-sight propagation. The statistical model of the additional delay τ is known, and the parameter τ obeys the exponential distribution, and its probability density function is:

$$P(\tau) = \begin{cases} 1/\tau_{rmsi} \exp\left(-\tau/\tau_{rmsi}\right), & \tau \geq 0 \\ 0, & \tau < 0 \end{cases} \tag{1}$$

where the τ_{rmsi} is the root mean square delay spread, which can be expressed as:

$$\tau_{rmsi} = T_1 d_i^{\varepsilon} \xi \tag{2}$$

In the formula (2), T_1 is the middle value of the τ_{rmsi} at d = 1000m, d_i is the distance between the mobile station (MS) and the base station (BS). The ε is an exponential component between the 0.5 $\sim$ 1 and a mean value of 0. The standard deviation σ_ξ is a logarithmic normal distribution of random variables between 4 $\sim$ 6 dB.

The arrival time of each base station detection signal contains two errors when the signal transmitted: the system error and channel environment error. The time that the signal reaches the i-th base station can be represented by the model of (3).

$$t_i = t_i^0 + \tau_i^0 + \tau_{i\min} \tag{3}$$

In the formula, t^0 is the line-of-sight signal propagation time, and τ^0 is the systematic error. It is a Gaussian random variable with a mean value of zero, namely $\tau^0 \sim N(0, \sigma_0^2)$, and σ_0 depends on the accuracy and detection means of the detection equipment. τ_{min} is the additional delay caused by the channel environment. It is a random variable closely related to the distance between the base station and the mobile station and the signal propagation environment. The difference in arrival time between two base stations i and j is:

$$\Delta t_{ij} = \left(t_i^0 - t_j^0\right) + \left(\tau_i^0 - \tau_j^0\right) + \left(\tau_{i\min} - \tau_{j\min}\right) \qquad i, j = 1, 2, \cdots, m \tag{4}$$

As can be seen from the formula (4), the error of the TDOA measurement value is mainly composed of two parts. The first part (τ_i^0-τ_j^0) is regarded as the Gauss random variable of the same distribution due to the τ_i^0 and the τ_j^0, therefore, the system error can be expressed as $\mu^0 \sim N(0, 2\sigma_0^2)$. The second part ($\tau_{imin}$-$\tau_{jmin}$) is an error caused by the channel environment. It is the most important part of the error, which is closely related to the channel environment and has a larger randomness, while the τ_{imin} and τ_{jmin} are exponentially distributed [22]. As the random phenomena cannot be described in a strict normal distribution, but if the factors of the determination are interdependent to a certain extent, or if they are not even and very small, they do not constitute a normal distribution. So it can only be approximated by the normal distribution of the class. In order to build closer to the real NLOS error model, the class normal distribution can be used to fit the channel environment error τ_{imin} and τ_{jmin}, which is exponential distribution, and the density function of the normal distribution of the additional time delay class is as follows [23]:

$$P\left(\tau_{i\,\min}\right)=\begin{cases}2\sqrt{2\pi}\sigma_i \exp\left(-\dfrac{\tau_{i\,\min}^2}{2\sigma_i^2}\right), & \tau_{i\,\min}>0\\ 0, & \tau_{i\,\min}\le 0\end{cases} \tag{5}$$

The basic idea of fitting the exponential distribution channel environment error with the normal distribution is to take the optimal estimation value of the parameter that minimizes the cumulative sum of squared error, which is the optimal estimation in the sense of least squares. Assuming that the sum of squared error accumulation is denoted as Q. For any set of observations $P(\tau_i)$, it satisfies:

$$Q=\sum_{i=1}^{n}\left(P\left(\tau_i\right)-P\left(\tau_{i\,\min}\right)\right)^2 \tag{6}$$

In the formula, $P(\tau_i)$ is a set of observations of the probability density curve with the additional time delay obeying the exponential distribution. The idea of optimal fitting in the sense of least squares can be made

$$\begin{cases}\left.\dfrac{\partial Q}{\partial \sigma_i}\right|_{(\sigma_i,\tau_{rmsi})}=0\\ \left.\dfrac{\partial Q}{\partial \tau_{rmsi}}\right|_{(\sigma_i,\tau_{rmsi})}=0\end{cases} \tag{7}$$

As can be seen from the formula (7), when $\sigma_i \approx \frac{1.22}{\sum_{i=1}^{n}(1/\tau_{rmsi})}$, the error of the class normal distribution is the most fitting of the error of exponential distribution, and the second part error (τ_{imin} -τ_{jmin}) in the error model can be approximated to the Gauss distribution that obeys zero mean, namely, $\mu_{ij} \sim N(0,\sigma_{ij}^2)$, and its variance is $\sigma_{ij}^2 = (\sigma_i^2+\sigma_j^2)/2$. In summary, the signal arrival time difference between two base stations is:

$$\Delta t_{ij}=\Delta t_{ij}^0+\mu \tag{8}$$

where, Δt_{ij}^0 is the real time difference of the signal arriving at two base stations. The error part can be written as $\mu \sim N(0,\sigma^2)$ and the variance is $\sigma^2 = 2\sigma_0^2+\sigma_{ij}^2$.

IV. TDOA/AOA HYBRID LOCATION ALGORITHM

If the TDOA location algorithm or the AOA location algorithm is used alone, the location effect is generally not ideal and the location error is large [24]. Moreover, if the two kinds of the localization algorithms are combined, the location accuracy can be significantly improved and the influence of measurement errors can be reduced [25], [26]. In this paper, we established a three orthogonal coordinate system for TDOA/AOA hybrid location, and discuss the problem of intranet location in the communication networks. In order to simplify the calculation, the base station coordinates are $(x_i,\ y_i,\ z_i)$, and the MS coordinates of the mobile station are (x, y, z).

Assume that a number of M base station receivers are arranged in a two-dimensional plane, the position coordinates of the *i-th* base station BS are represented by (x_i, y_i), the positions of the mobile station MS are represented by coordinates (x, y), the distance from the mobile station to the base station is r_i, and the distance equation can be listed according to the measured values obtained by the TOA location algorithm:

$$r_i=c\tau_i=\sqrt{(x_i-x)^2+(y_i-y)^2} \tag{9}$$

In the formula (9), c is the radio propagation speed and τ_i is the time difference. In general, the reference base station is selected as the first base station, and the measured value of the arrival time difference TDOA is converted to the distance difference $r_{i,1}$, $r_{i,1}$ which indicates the difference between the mobile station to the base station $i(i\ \neq 1)$and the base station 1, that is:

$$r_{i,1}=r_i-r_1+n_{i,1}=\sqrt{(x_i-x)^2+(y_i-y)^2}-\sqrt{(x_1-x)^2+(y_1-y)^2}+n_{i,1} \tag{10}$$

As shown in formula 10, $i\ =\ 2,3,..,M$, $n_{i,1}$ is the noise introduced during location measurement. $n_{i,1}=n_i$-n_1, n_i is the measurement errors of the system, r_1 is the distance from base station 1 to the mobile station MS [27]. When the signal-to-noise ratio is high, it can be considered that the measured values of TDOA are approximately normal distribution. therefore, $n_{i,1}$ can also be considered as the approximately normal distribution. Assuming that the mean value is 0 and the variance is σ^2. At the same time, the base station can always provide the measurement value of the AOA location algorithm of MS, according to the measurement value of the AOA location algorithm, the equation can be established:

$$\tan\alpha=\frac{y-y_1}{x-x_1}+n_\alpha \tag{11}$$

In the formula (11), n_α is the measurement error of AOA, assuming that it obeys the normal distribution with a mean value of 0 and a variance of α^2. Suppose $\Delta r\ =[r_{2,1}, r_{3,1},\ldots r_{M,1}]^{\mathrm{T}}$, $r\ =[r_2, r_3,\ldots r_M]^{\mathrm{T}}$, $r_1\ =[r_1, r_1,\ldots, r_1]^{\mathrm{T}}$, $n\ =[n_{2,1}, n_{3,1},\ldots n_{M,1}]^{\mathrm{T}}$, and according to the above formula, can be obtained:

$$\Delta r=r-r_1+n \tag{12}$$

In this paper, the maximum likelihood method is used to determine the coordinates of the mobile platform MS, because of the $r_{i,1}$ obeys the normal distribution of (r_i-r_1) and the variance of σ^2, α is subjected to the normal distribution of arctan $((y-y_1)/(x-x_1))$ and the variance is α^2. Assuming that the measured values are independent of each other, the maximum likelihood estimation of the position of the mobile station is

$$(x,y) = \arg\min[(\Delta r - r + r_1)^T (\Delta r - r + r_1) + \frac{\sigma^2}{\alpha^2}\left(\alpha - \arctan\left(\frac{y-y_1}{x-x_1}\right)\right)^2] \quad (13)$$

For the nonlinear equation (13), it is difficult to obtain the ideal result by the general method. Therefore, the chaotic theory optimized particle swarm optimization algorithm (CPSO) is used to solve the optimal solution of the population position and obtain the optimal location estimation of the location algorithm.

V. PARTICLE SWARM OPTIMIZATION BASED ON CHAOS THEORY

A. PSO ALGORITHM

Particle swarm optimization (PSO) is an evolutionary algorithm in the class of swarm intelligence optimization algorithms [28], [29]. It has the following advantages: (1) Its convergence speed is fast, it can quickly yield the search results; (2) It requires only a few control parameters, and thus is simple and easy to implement; (3) It can be easily realized via parallel computing since its operations are applied to a group of particles [30], [31]. The basic idea is that a set of initialized random particles of a system, each particle, is a possible solution to the existence of the objective function, and the optimal solution is obtained by calculating and analyzing some iteration manner [32]. That is, the optimal solution represents the estimated position of the mobile station MS.

The implementation steps of the PSO algorithm: the number of particles in a population is S, in the d dimension space. $U = (u_{k1}, u_{k2}, \ldots u_{kd})$ and $Y = (y_{k1}, y_{k2}, \ldots, y_{kd})$ represent the velocity and position of the K particle, respectively. Where $k = 1, 2, \ldots, S, p = 1, 2, \ldots, d$, that is, P is a dimension, $y_{kp} \in [L_p, H_p]$, L_p and H_p represent the lower and upper bounds of spatial dimensions, respectively. $u_{Sd} \in [U_{min,d}, U_{max,d}]$, $U_{min,d}$ and $U_{max,d}$ represent the minimum velocity and maximum velocity of particles respectively. Using $Q_k = (q_{k1}, q_{k2}, \ldots, q_{kd})$ represents the optimal solution of the K particle, and $Q_g = (q_{g1}, q_{g2}, \ldots, q_{gd})$, it represents the global optimal solution of all species and updates the velocity vectors and position vectors of each particle according to formula (14) and (15).

$$u_{kp}(z+1) = \omega u_{kp}(z) + c_1 r_1 \left(q_{kp}(z) - y_{kp}(z)\right) + c_2 r_2 \left(q_{gp}(z) - y_{kp}(z)\right) \quad (14)$$

$$y_{kp}(z+1) = y_{kp}(z) + u_{kp}(z+1), p = 1, 2, \cdots, d \quad (15)$$

$$\begin{cases} y_{kp}(z+1) = 1, r(z+1) < sigmoid\left(u_{kp}(z+1)\right) \\ y_{kp}(z+1) = 0, r(z+1) \geq sigmoid\left(u_{kp}(z+1)\right) \end{cases} \quad (16)$$

As shown in the formula (14), c_1 and c_2 are acceleration factors respectively; the number of current iterations is z, the maximum number of iterations is T; r_1 and r_2 take the random number between [0,1]; $r(z+1)$ is the real number generated between [0,1] in the z-th iteration, of which the sigmoid function is:

$$sigmoid\left(u_{kp}(z+1)\right) = \begin{cases} 0.98 & u_{kp}(z+1) > 3 \\ \frac{1}{1+e^{-u_p(z+1)}} & -3 \leq u_{kp}(z+1) \leq 3 \\ -0.98 & u_{kp}(z+1) < 3 \end{cases} \quad (17)$$

ω is the inertia factor and its value is:

$$\omega = \omega_{\max} - \frac{z(\omega_{\max} - \omega_{\min})}{T} \quad (18)$$

In the formula (18), with the iterative evolution of particles, $\omega \in (\omega_{min}, \omega_{max})$ gradually decreases from large to small [33].

B. THE FITNESS FUNCTION

The fitness function is the basis of chaotic optimized particle swarm algorithm to guide search direction. In the proposed algorithm, the best corresponding coordinates (x, y) are mobile station coordinates. The fitness function is as follows:

$$Fitness(Y) = sqrt[(\Delta r - r + r_1)^T (\Delta r - r + r_1) + \frac{\sigma^2}{\alpha^2}\left(\alpha - \arctan\left(\frac{y-y_1}{x-x_1}\right)\right)^2] \quad (19)$$

The smaller the fitness value, the better to the function of the particle's adaptability. The optimal location of the particle k is determined by formula (20):

$$q_{kp}(z) = \begin{cases} q_{kp}(z-1), & fitness\left(y_{kp}(z)\right) \geq fitness\left(q_{kp}(z-1)\right) \\ y_{kp}(z), & fitness\left(y_{kp}(z)\right) < fitness\left(q_{kp}(z-1)\right) \end{cases} \quad (20)$$

The global optimal position of the particle k is determined by the formula (21).

$$q_{gk}(z) \in \left\{q_{g1}(z), \cdots, q_{gs}(z) \,|fitness\left(q_{gs}(z)\right) = \min\left\{fitness\left(q_{g1}(z)\right), \cdots |fitness\left(q_{gs}(z)\right)\right\}\right\} \quad (21)$$

The coordinate vector of a particle is defined as

$$\psi_i = (x_i, y_i)^T \quad (22)$$

As shown in formula (22), (x_i, y_i) is the coordinate point to be estimated by the mobile station. The coordinates of the mobile station are (x, y) in the range of the base station.

$$\begin{cases} x_{\min} \leq x \leq x_{\max} \\ y_{\min} \leq y \leq y_{\max} \end{cases} \quad (23)$$

As shown in the formula (23), x_{min} and x_{max} are the minimum and maximum values of the transversal coordinates in the range of the base station, and y_{min} and y_{max} are the minimum and maximum values of the ordinates within the range of the base station.

C. THE IMPLEMENTATION OF CPSO ALGORITHM

Although the particle swarm algorithm has the above advantages, it also has some disadvantages. Asin the intelligent optimization algorithms that have the same problem: they are prone to premature convergence and fall into a local optimal solution. For the multi-peak function to solve the global optimal solution is relatively poor, but in practices the emergence of such optimization problems is also quite common. Therefore, in the practical application of the PSO algorithm needs to be improved to a certain extent, in order to avoid its premature phenomenon and fall into the local optimum [34].

Chaos theory is a random motion state obtained from the determined equations. The chaotic optimization algorithm generates a set of random sequences by using the chaotic equation, which is used for random traversal search. The characteristics of chaotic algorithms are: (1) randomness, the chaotic variable generated by the algorithm is as random as random variables; (2) ergodicity, the random sequence generated by the algorithm cannot repeat all points in the search area. (3) regularity, the algorithm is controlled by determining the iterative equation; (4) it is very sensitive to the initial value, and the minor changes of initial conditions will cause great changes in system behavior [35].

The basic idea of the proposed algorithm is: using the characteristics of randomness, regularity and ergodicity of the chaos theory, the optimal solution found in the whole population is the initial value, and the chaotic sequence is generated, Moreover, the particle of the optimal value in the chaotic sequence is interchanged with the particle in the current particle swarm. This will be an efficient optimization algorithm that can solve the problems existing in particle swarm optimization and achieve the effect of fast convergence.

There are many existing chaotic models. By comparing with the different models, we found that the logic self-mapping function has good characteristics. The classical logistic equation (24) is used in this paper, and the expression is as follows:

$$Z^{i+1} = \mu Z^i \left(1 - Z^i\right) \quad Z^i \in (0, 1) \tag{24}$$

In the formula (24), $\mu \in$ (2,4], and it is used as the control parameter, and the larger of the value is, the larger of the proportion by the chaos. When the Z^i is determined, the time sequence can be iterated.

In the traditional PSO algorithm, r_1 and r_2 in the equations (14) and (15) for the initializing population particles appear as the random numbers. That is, the initial velocity and the direction of each particle in the population are indefinite and irregular, and thus there are some spatial positions that will be missed, which cannot guarantee the ergodicity in the optimization process and the diversity of the entire space. Therefore, the chaotic mapping is performed when the particle's velocity and position are initialized at the beginning of the algorithm. That is to say, instead of using r_1 and r_2, two chaotic sequences generated by equation (16) are used to improve the algorithm's optimization performance by using the ergodicity characteristics of chaos theory.

The steps of chaotic optimized PSO algorithm are as follows:

1) The parameters of PSO algorithm are initialized: the population size S, the maximum iteration number T, the acceleration factor are c_1 and c_2, the maximum inertia factor is ω_{max} and the minimum inertia factor is ω_{min}, the inertia factor ω is calculated by the formula (18).

2) The velocity vectors and position vectors of each particle are updated according to equations (14) and (15). Ensure that in the $[v_{min,D}, v_{max,D}]$ of the speed range, if it exceeds the upper and lower limits, then change to $v_{min,D}$ and $v_{max,D}$.

3) Calculate the fitness value of each particle according to the fitness function formula (19).

4) The chaotic perturbation of the global optimal value of the population $Q_g = (q_{g1}, q_{g2}, \ldots, q_{gd})$ is performed and the Q_g is normalized:

$$Z_p = \frac{q_{gp} - q_{gp\,\min}}{q_{gp\,\max} - q_{gp\,\min}}, \quad p = 1, 2, \cdots, d \tag{25}$$

As shown in equation (25), q_{gpmax} and q_{gpmin} represent the maximum and minimum values of the p-th dimensional variable q_{gp}. The chaotic sequence generated by using the formula (24) converse it through the following (26).

$$q_{gp}^m = q_{gp,\min} + Z_p^m \left(q_{gp,\max} - q_{gp,\min}\right), \quad p = 1, 2, \cdots, d \tag{26}$$

Then return to the original solution space, available:

$$Q_g^m = \left(q_{g1}^m, q_{g2}^m, \cdots, q_{gd}^m\right), \quad m = 1, 2, \cdots, d \tag{27}$$

In the original solution space, the fitness value is calculated for the feasible solution Q_g^m experienced by each chaotic variable, and the optimal value with the least fitness is taken as the new global optimal value.

6) When the number of iterations reaches T, stop the iteration and get the optimal solution, otherwise, skip to step 2.

VI. SIMULATION COMPARISON AND PERFORMANCE ANALYSIS

The simulation experimental environment of the proposed algorithm is based on the MATLAB 2014a software platform, and the simulated computer is a 64-bit system based on Windows 7. In this paper, the Taylor algorithm, the Chan algorithm, the TDOA/AOA hybrid location algorithm and the CPSO algorithm proposed in this paper are used to compare the positioning accuracy and the performance of the algorithm [15]. Since the positioning performance of mobile communication networks based on three base stations is generally not good, the number of base stations selected in this paper exceeds three. The main parameters of the simulation experiment in this paper are as follows: using a honeycomb structure with 9 receivers, the number of base stations is selected between 4 and 9, the cell radius is selected as 3000m, the serving base station is BS1, and the coordinates of the base station

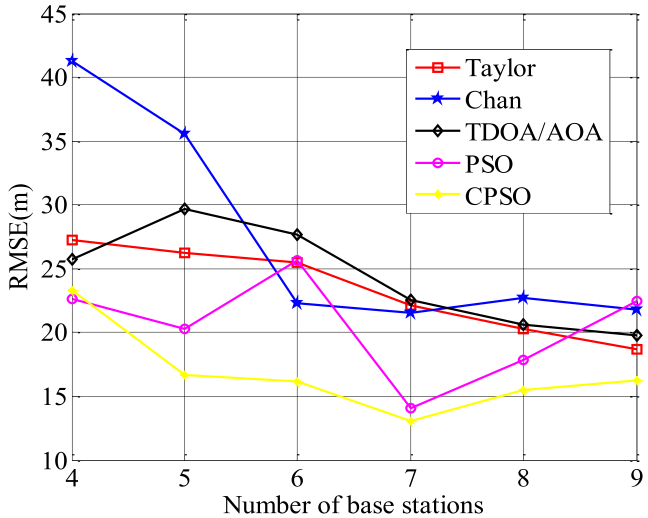

FIGURE 5. **The relationship between the location error and the number of base stations.**

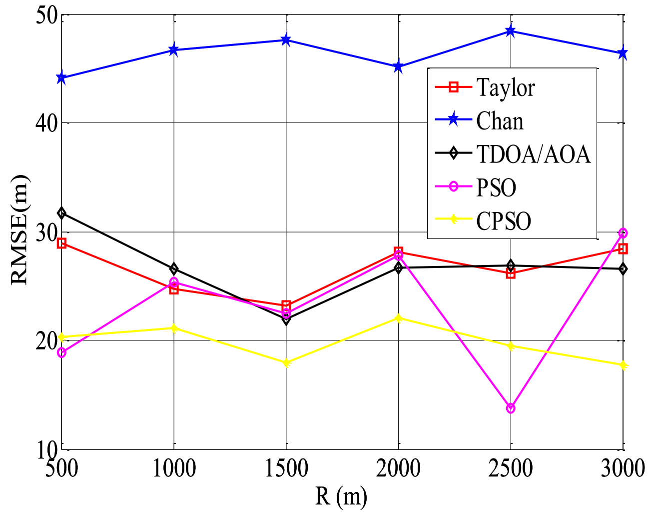

FIGURE 6. **The relationship between the location error and the communication radius.**

are selected as follows: BS1(0,0), BS2($-\sqrt{3}$, 0), BS3($\sqrt{3}$, 0), BS4($\sqrt{3}/2, 3/2$), BS5($-\sqrt{3}/2, -3/2$), BS6($-\sqrt{3}/2, 3/2$), BS7($\sqrt{3}/2, -\sqrt{3}/2$), BS8(0,2), BS9($0, -2$). Since the TDOA measurement error obeys the mean value of 0, and the variance takes the Gauss normal distribution of 30m, 60m, 90m, 120m and 150m respectively. The channel model of the NLOS error caused by the channel environment, the AOA measurement error obeys the Gauss normal distribution with a mean value of 0. The learning factor c_1 and c_2 of the PSO algorithm are 2.4, the initial inertia value ω_{max} is 0.9, the inertia weight of the iteration value ω_{min} is 0.2, the initial particle number is 60, and the iteration number is 50 times.

(1) The location performance is affected by the number of base stations, cell radius and measurement error, and the initial coordinates of the mobile station are set to (0.8, 0.2).

1) The location performance is affected by the number of base stations. From Figure 5, we can see that when the error is 30m, the radius is 3000m, and with the increase of base stations from 4 to 9, the different location accuracy of each algorithm is shown in Figure 5.

As shown in Figure 5, when the number of base stations is $4 \sim 6$, the PSO algorithm's curve is obviously lower than the other three algorithms, and its location performance is the best and the Taylor algorithm is the second. When there are $7 \sim 9$ base stations, the difference between the location performances is not large, and the overall average value is small. Compared with Taylor algorithm, Chan algorithm and TDOA/AOA algorithm, the positioning accuracy of CPSO algorithm are improved significantly. The smoothness of the CPSO algorithm presented in this paper reflects the better stability of the algorithm.

2) The location performance is affected by the communication radius. The measurement error is 30m, the communication radius is 500m to 3000m, and the number of the base station is 7. The location accuracy of the four algorithms is constantly changing and the standard error is reduced, as shown in Figure 6.

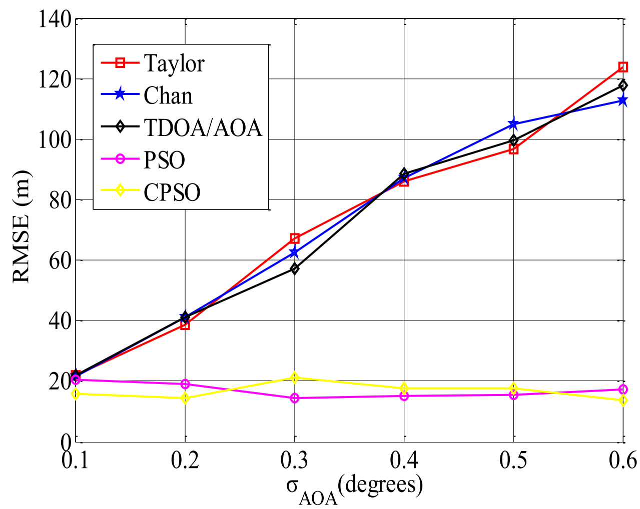

FIGURE 7. **The relationship between standard error and measurement error.**

From Figure 6, we can see that with the increasing communication radius, location error is increased. At the same time, the location performance and reliability of the CPSO algorithm are superior to the other three location algorithms. This is because the chaotic particle swarm optimization algorithm is to optimize the function of TDOA/AOA, eliminate certain errors, reduce the error caused by the change of the radius to a certain extent, and improve the location accuracy.

3) the location performance is influenced by the measurement error. When the radius takes 3000m and the base station takes 7, the error variance is from 30m to 240m, the transverse coordinates are x $= \sigma_{AOA} \times c$, c is the speed of light. With the increase of measurement error, the location accuracy of each algorithm is changed, as shown in Figure 7.

As can be seen from Figure 7, the standard errors of the other three algorithms also increase. At the same time, the chaotic particle swarm optimization algorithm is not affected by the error before the error is less than 120m,

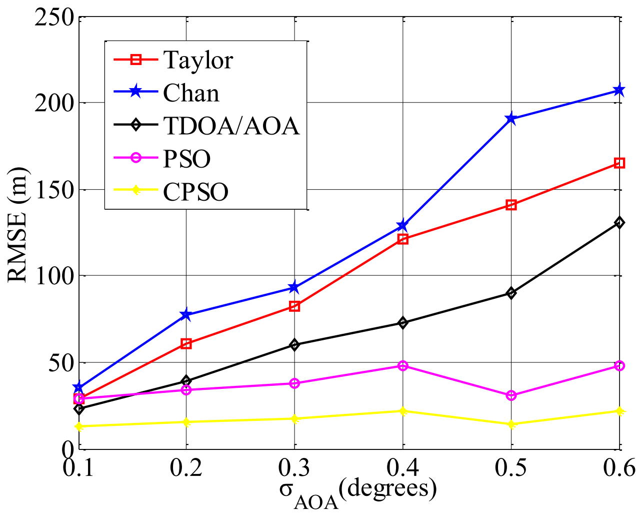

FIGURE 8. The relationship between standard deviation and measurement error.

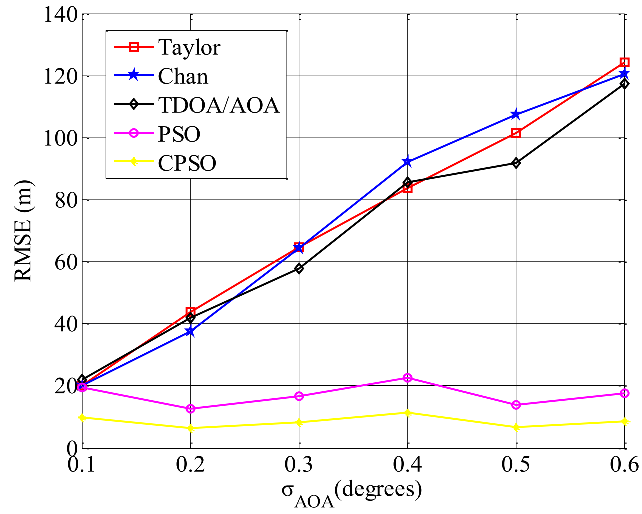

FIGURE 9. The relationship between location error and measurement error in different reference coordinates.

compared to the other three algorithms. This is because the chaos theory can effectively suppress the influence of the error on the location accuracy, and the location performance is obviously improved. The other three methods are greatly influenced by the error. As the measurement error increases, the probability that the final measurement result will show a deviation will be greater, and the performance of the algorithm will be more unstable.

(2) In addition, we do simulation analysis and verification from two other aspects. On the one hand, the number of different base stations will have great influence on the location accuracy under different measurement errors. When the number of base stations is too small, the accuracy of measurement data will be greatly affected. When the number of base stations is too large, the amount of data will increase and the computation will be complicated. On the other hand, the choice of initial location of mobile station has great influence on location accuracy.

1) When the communication radius is 3000m and the number of base stations is 4, the relationship between measurement error and standard error is shown in Figure 8.

As can be seen from Figure 8, the standard deviation of the 4 location algorithms is increasing gradually, which shows that the standard error is greatly influenced by the number of base stations, and the reduction of base station will make the measurement value of TDOA and AOA to be not accurate enough, and the error will increase.

2) When the number of base stations is 7 and the reference coordinates (0.8, 0.6) is selected, the relationship between the measurement error and the standard error is shown in Figure 9.

From Figure 9, it can be seen that the reference coordinates have great influence on the location performance of the CPSO algorithm. The proposed algorithm has a good performance and higher location accuracy when it is near the center of the base station. Therefore, the selection of the reference

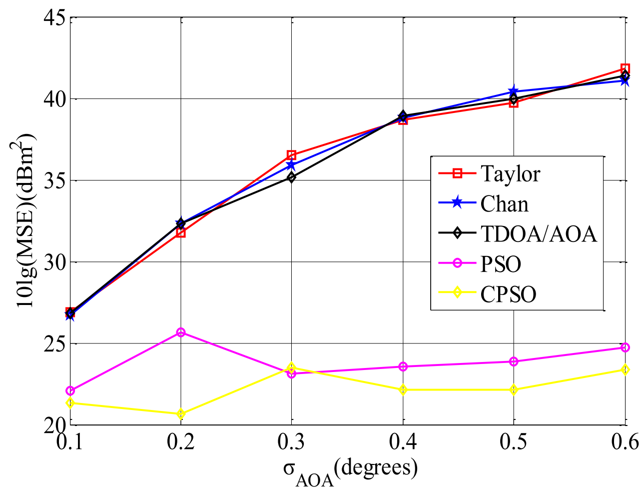

FIGURE 10. The relationship between measurement error and mean square error.

coordinates can make the location algorithm better in the measurement process.

(3) The relationship between measurement error, communication radius, base station number and mean square error. Set the abscissa coordinates for measurement error, base station number, communication radius, and the ordinate $y = 10\lg(\mathrm{MSE})$. The position estimation MSE is calculated through 200 experiments according to formula (28):

$$MSE = \frac{\sum_{L=1}^{200} \|\tilde{x}(l) - x\|_2^2}{200} \tag{28}$$

In the formula (28), the estimated position value of x in $\tilde{x}(l)$ by one time. The measurement results are shown in figures (10), (11), and (12).

It can be seen from Figure 10, as the measurement error increases, the mean square error also increases. The CPSO algorithm shows good location performance in mean

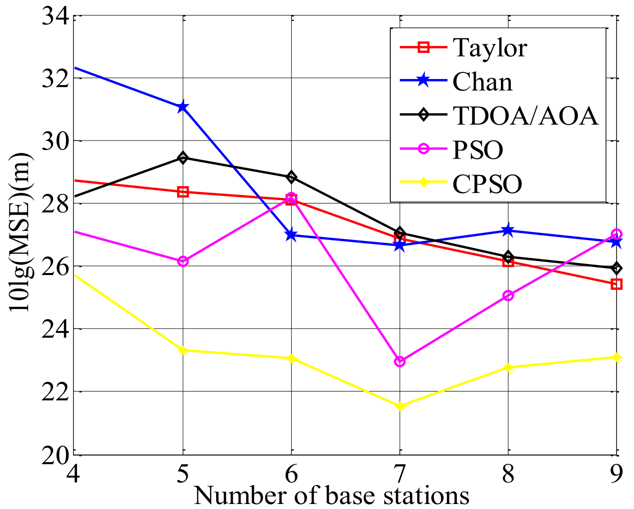

FIGURE 11. The relationship between the number of base stations and the mean square error.

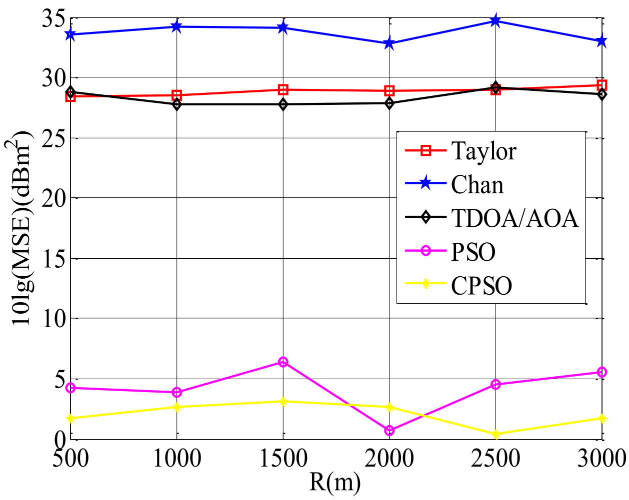

FIGURE 12. The relationship between the communication radius and the mean square error.

square error. This is because the chaos particle swarm algorithm reduces the measurement error. The impact on location makes location more accurate.

It can be seen from Figure 11 that the accuracy of the CPSO algorithm proposed in this paper is significantly higher than that of the other three base stations before the six base stations. After the number of base stations is greater than six, the accuracy is not affected by the number of base stations. The reason is that the TDOA measurement value between the BS and the MS is corrected. In this case, the measurement deviation of the AOA acts on the location performance.

As can be seen from Figure 12, we can see that the CPSO algorithm proposed in this paper performs better than the other three algorithms. This is because the chaos theory is added to the particle swarm optimization algorithm, and the ergodicity is used to avoid linearization in the operation process, and then the algorithm gets into the local optimal

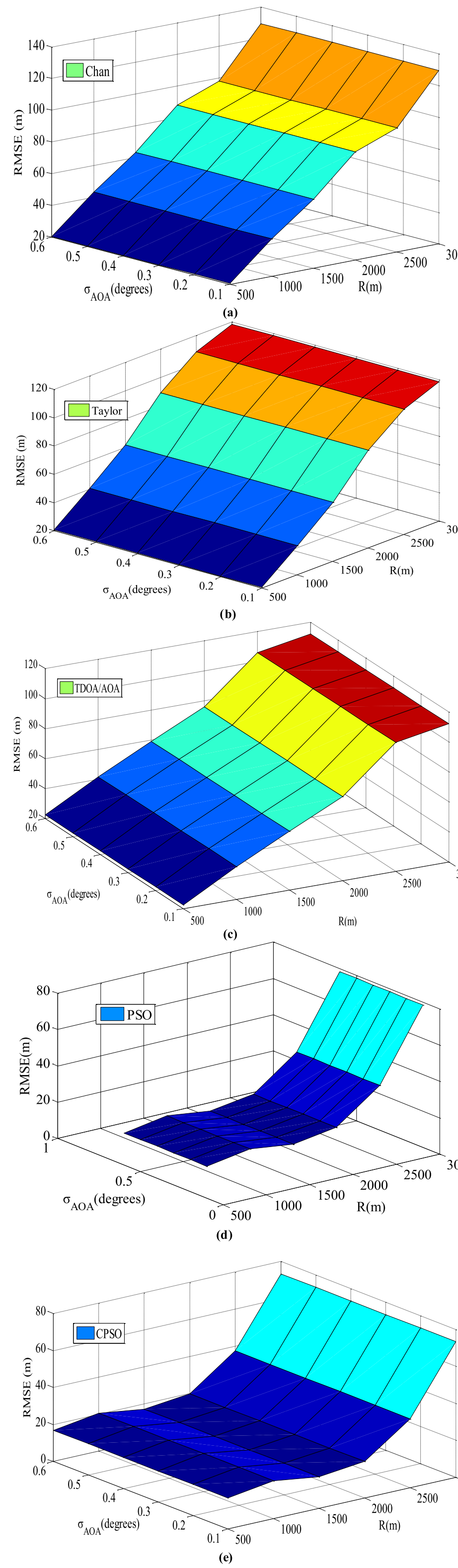

FIGURE 13. Results of three dimensional location errors of four algorithms. (a) Three-dimensional location error of Chan algorithm. (b) Three-dimensional location error of Taylor algorithm. (c) Three-dimensional location error of TDOA/AOA hybrid location algorithm. (d) Three-dimensional location error of PSO hybrid location algorithm. (e) Three-dimensional location error of CPSO hybrid location algorithm.

TABLE 1. Comparison of simulation time consumption of five algorithms.

The localization algorithm	Simulation time consuming (s)
Chan algorithm	2.64
Taylor algorithm	3.95
TDOA/AOA algorithm	5.27
PSO algorithm	6.59
CPSO algorithm	7.91

solution, which makes the location performance of the TDOA/AOA hybrid location improved. Therefore, the CPSO algorithm can be used in TDOA/AOA hybrid location, which can overcome the nonlinear problems and improve the location accuracy.

(4) Comparison and analysis of 3D spatial location error

On the basis of two-dimensional space, this paper compares the location performance of the Taylor algorithm, the Chan algorithm, the TDOA/AOA hybrid algorithm and our proposed algorithm are compared from the angle of three-dimensional space location. The results of three dimensional location algorithms are shown in figures 13 (a), (b), (c) and (d) respectively.

From the comparison of the three-dimensional positioning errors of these five algorithms, it can be seen that with the increase of measurement error and communication radius, the root mean square error of the four algorithms, such as the Taylor algorithm, the Chan algorithm, the TDOA/AOA hybrid algorithm, the PSO algorithm, the CPSO algorithm and so on, increases. However, the maximum location error of the Taylor algorithm reaches 135m, the maximum error of the Chan algorithm reaches 120m, and the hybrid location error 115m of the TDOA/AOA hybrid algorithm is 115m. The maximum error of the proposed algorithm is 80m, and the error of the Chan algorithm is much smaller than that of the other three kinds of location algorithms. It can be seen that the location error of CPSO algorithm proposed in this paper is the smallest and the location effect is the best.

Finally, we compare the simulation time of the five algorithms, as shown in Table 1.

It can be seen from the simulations time-consuming comparison of the five algorithms in Table 1. The Chan algorithm takes the least time, the Taylor algorithm takes less time, and the PSO location algorithm simulation takes more time. The proposed algorithm CPSO takes the most time. This is mainly because the chaos algorithm needs to be optimized first, and the simulation takes more time than the PSO algorithm, but not many.

VII. CONCLUSION

In this paper, the TDOA/AOA hybrid location of chaotic optimized particle swarm optimization algorithm is deeply studied in mobile location estimation. By using the chaos theory to improve and optimize the PSO algorithm, and locate the target function of TDOA/AOA as the fitness function, the mathematical modeling and optimization of the fitness function were performed, and the coordinate points corresponding to the optimal fitness are solved. And the measurement error and nonlinear optimization problem in TDOA/AOA hybrid positioning are effectively solved. From the analysis and simulation results, we can see that, compared with the traditional Taylor algorithm, the Chan algorithm and the TDOA/AOA hybrid algorithm, the chaotic optimizated particle swarm optimization (PSO) algorithm proposed in this paper has the higher location accuracy and stability under the different communication radius and the measurement error. At the same time, because of it's simple algorithm and easy implementation, the TDOA/AOA hybrid location algorithm based on CPSO has very important research significance in practical application.

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