A Parallel Particle Swarm Optimization Algorithm for Reference Stations Distribution

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***Abstract*—Parallel Particle Swarm Optimization (PPSO) algorithm is proposed to optimize the reference stations distribution and this algorithm will increase the User Differential Range Error (UDRE) accuracy and enhance the flight safety. Due to the reference stations distribution largely influence the accuracy of UDRE, a concept of Satellite Surveillance Dilution of Precision (SSDOP) is used to reflect the effect of changing the reference stations distribution on UDRE. After analyzing the expressions of SSDOP and UDRE, UDRE is influenced by restriction factor and SSDOP when measurement noise is a certain value, and the restriction factor is independent on SSDOP. Then, a mathematical equation between SSDOP and UDRE is deduced from the SSDOP and UDRE expressions, and a linear trend is showed. A Particle Swarm Optimization (PSO) algorithm is proposed, and it first randomly generates a group of particles and each particle represents a reference stations distribution. The average SSDOP is used as the fitness function to evaluate each particle. Both the local best and global best are used to guide the search direction. However, the proposed PSO algorithm may converge too fast which makes the optimizing result to become the local optimization. Thus, the PPSO algorithm with parallel computing is proposed to overcome this problem. Experiments are made to compare the performance of the proposed PPSO algorithm, the proposed PSO algorithm, "*N-Angled*" method and Exhaustive Grid Search method. The proposed PPSO algorithm can find the best solution without falling in local optimization, and isn't restricted by the state and amount of the satellites and the outline of the searching area.**

***Index Terms*—UDRE, reference stations distribution, SSDOP, PSO, parallel computing, flight safety**

I. Introduction

As the fast development of aviation industry, flight safety becomes more and more important. Flight accidents are the results of multi-factors, such as poor positioning accuracy without warning. Satellite Based Augmentation System (SBAS), however, can improve flight safety by providing satellites' integrity and correction data to SBAS flight users.

Integrity data (such as User Differential Range Error, UDRE) is used to calculate Horizontal Protection Level (HPL) or/and Vertical Protection Level (VPL) which are the reflection of the Horizontal Protection Error (HPE) and Vertical Protection Error (VPE) representing the positioning accuracy. The user receiver compares the protection levels with the alert limits. If one of the protection levels exceeds the corresponding alert limit, the receiver provides an annunciation to the pilot [1]. Thus, UDRE makes a preeminent contribution to the safety of flight.

The reference stations collect measurements from the Global Positioning System (GPS) and SBAS satellites to determine UDRE and correction data. The distribution of the reference stations network, therefore, has a great impact on the accuracy of UDRE. Accordingly, how to find a good reference stations distribution becomes the most important thing.

In this paper, a conception of Satellite Surveillance Dilution of Precision (SSDOP) is proposed to reflect the impact on the satellite's UDRE by changing the reference stations distribution. And according to the UDRE calculation method introduced below, UDRE is influenced by restriction factor and SSDOP when measurement noise is a certain value. Then, experiments are made to find that the restriction factor is independent on SSDOP but only influenced by the latitude and longitude of the satellite footprint. Thus, a mathematical equation relating SSDOP and UDRE is deduced where a linear trend is exhibited.

Compared with UDRE, SSDOP is easier to calculate which only needs the unite vectors from the reference stations to the satellite. So the average SSDOP of satellites is chosen as the fitness function. Then, the proposed Particle Swarm Optimization (PSO) algorithm using average SSDOP as its fitness function is given to optimize the distribution of reference stations. However, there is a shortcoming of this proposed PSO algorithm. Sometimes, the proposed algorithm may converge too fast which makes the optimizing result to become the local optimization. Therefore, a Parallel Particle Swarm Optimization (PPSO) algorithm for optimizing distribution is proposed to solve this problem.

Finally, experiments are made to compare the performance of the PPSO method ,the proposed PSO

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method and that of other methods. The correlative results indicate that the PPSO method is quite suitable for optimizing reference stations distribution in SBAS.

II. RELATIONSHIP BETWEEN SSDOP AND UDRE

SBAS is a combination of ground-based and space-based equipments that augments the GPS. A network of ground reference stations with precisely surveyed GPS antennas is strategically positioned to collect GPS satellite data across the service volume. In each reference station, the code and carrier phase measurements are obtained by the dual frequency (cross-correlating) receivers and the pseudo-range residual error is calculated using the measurements. Then, the residual error of every reference station is sent to the master station where generates the ephemeris and clock corrections and UDRE.

A. UDRE Algorithm

According to [2], the reference stations' observations are used as the inputs of Weighted Least Square (WLS) estimator to calculate the satellite ephemeris and clock corrections and variances. These outputs of the estimator, then, are used to calculate UDRE. The flow chart of UDRE is showed in Fig. 1.

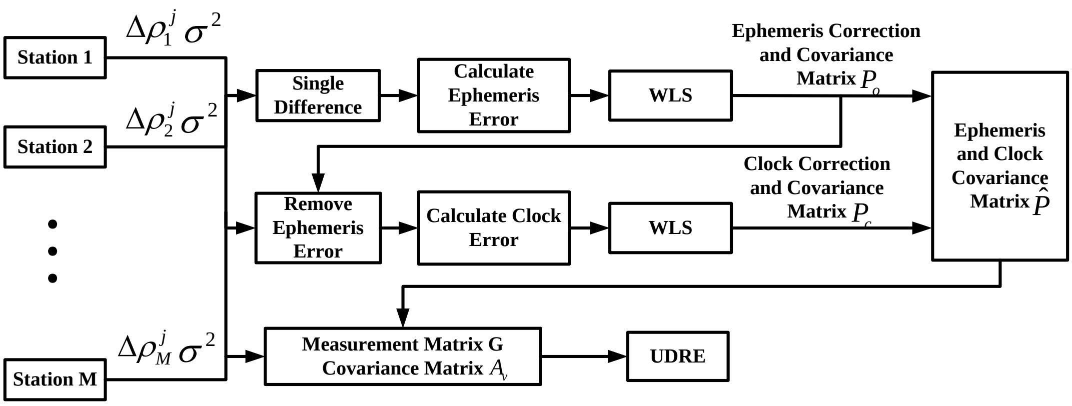

Figure 1. The flow chart of UDRE

To be specific, pseudo-range residual is computed by removing geometric range, satellite clock bias, ionospheric delay and tropospheric delay from the carrier smoothed pseudo-range. At this point, the pseudo-rang residual merely includes the ephemeris error, the satellite clock error and measurement noise as follow:

$$\Delta\rho_i^j = \Delta\vec{R}^j \bullet \vec{l}_i^{\,j} - \Delta B^j + v_i^j \tag{1}$$

where $\Delta\rho_i^j$ is the pseudo-range residual for the j^{th} satellite at the i^{th} reference station; $\Delta\vec{R}^j$ and ΔB^j ,respectively, are the ephemeris error vector and the clock error of the j^{th} satellite; $\vec{l}_i^{\,j}$ is the unit line of sight vector from the reference station to the satellite and v_i^j is the measurement noise which accounts for the error in carrier smoothing, ionospheric delay estimation and tropospheric delay estimation with a standard deviation of σ .

To separate the satellite clock error from the ephemeris error, single differencing is needed. Although directly computing both $\Delta\vec{R}^j$ and ΔB^j simultaneously is possible and the corrections can provide adequate integrity and availability for the users, doing so will let ephemeris and clock corrections be sent together and this will take up too much broadcast bandwidth.

After single differencing, the satellite clock error is removed from the pseudo-range residual. The expression is as below:

$$\Delta\rho_{os} = H_{os}\Delta\vec{R}^j + V_{os} \tag{2}$$

where $\Delta\rho_{os} = \begin{bmatrix} \Delta\rho_1^j - \Delta\rho_k^j & \cdots & \Delta\rho_M^j - \Delta\rho_k^j \end{bmatrix}^T_{(M-1)\times 1}$; $H_{os} = \begin{bmatrix} \vec{l}_1^{\,j} - \vec{l}_k^{\,j} & \cdots & \vec{l}_M^{\,j} - \vec{l}_k^{\,j} \end{bmatrix}^T_{(M-1)\times 3}$; V_{os} is a noise matrix with a covariance matrix $A_{os} = 2\sigma^2 I_{(M-1)\times(M-1)}$; M is the number of reference stations that observe the j^{th} satellite.

Then, a WLS estimator is used to estimate ephemeris error from (2). The satellite ephemeris correction and its accuracy can be written as:

$$\Delta\hat{\vec{R}}^j = (H_{os}^T A_{os}^{-1} H_{os})^{-1} H_{os}^T A_{os}^{-1} \Delta P_{os} \tag{3}$$

$$\begin{aligned} P_o &= \begin{bmatrix} H_{os}^T A_{os}^{-1} H_{os} \end{bmatrix}^{-1}_{3\times 3} \\ &= 2\sigma^2 \begin{bmatrix} H_{os}^T H_{os} \end{bmatrix}^{-1}_{3\times 3} \end{aligned} \tag{4}$$

Derived from (1) and (3), the expression used to compute satellite clock correction is expressed as follow:

$$\Delta\rho_c = H_c \Delta B^j + V_o \tag{5}$$

where $\Delta\rho_c = H_o \Delta\hat{\vec{R}}^j - \Delta\rho_{o,c}$, $\Delta\rho_{o,c} = \begin{bmatrix} \Delta\rho_1^j & \cdots & \Delta\rho_M^j \end{bmatrix}^T$, $H_o = \begin{bmatrix} \vec{l}_1^{\,j} & \vec{l}_2^{\,j} & \cdots & \vec{l}_M^{\,j} \end{bmatrix}^T_{M\times 3}$, $H_c = \begin{bmatrix} 1 & 1 & \cdots & 1 \end{bmatrix}^T_{M\times 1}$; the covariance matrix of V_o is $A_o = H_o P_o H_o^T + A_v$, $A_v = \sigma^2 I_{M\times M}$.

Just like the calculation of the satellite ephemeris correction, the clock correction is computed in a WLS estimator as well. The expressions of clock correction and its accuracy are as below:

$$\Delta\hat{B}^j = \left(H_c^T A_o^{-1} H_c\right)^{-1} H_c^T A_o^{-1} \Delta P_c \tag{6}$$

$$\begin{aligned} P_c &= \left[H_c^T A_o^{-1} H_c\right]_{1\times1}^{-1} \\ &= \sigma^2 \left[H_c^T \left(2H_o \left(H_{os}^T H_{os}\right)^{-1} H_o^T + I\right)^{-1} H_c \right]_{1\times1}^{-1} \end{aligned} \tag{7}$$

After attacking the computation of the correction data, the error vector after using ephemeris and clock corrections is $\vec{\varepsilon}^{\,j} = [\Delta\vec{R}^j \quad \Delta B^j]^T - [\Delta\hat{\vec{R}}^j \quad \Delta\hat{B}^j]^T$. Because of the calculation of the satellite ephemeris and clock corrections are apart, the $\Delta\hat{\vec{R}}^j$ and $\Delta\hat{B}^j$ are independent on each other and the correlation coefficient between $\Delta\hat{\vec{R}}^j$ and $\Delta\hat{B}^j$ is zero. Then, the covariance matrix of $\vec{\varepsilon}^{\,j}$ is expressed as below:

$$\hat{P} = \begin{bmatrix} P_o & 0 \\ 0 & P_c \end{bmatrix} \tag{8}$$

The true value of $\vec{\varepsilon}^{\,j}$ is unknown and the estimation of the correction data is mainly influenced by measurement noise, thus the covariance matrix for combined ephemeris and clock error estimates are computed as follow:

$$\begin{aligned} P_{UDRE} &= A_v + G\hat{P}G^T \\ &= A_v + \begin{bmatrix} H_o & H_c \end{bmatrix} \begin{bmatrix} P_o & 0 \\ 0 & P_c \end{bmatrix} \begin{bmatrix} H_o^T \\ H_c^T \end{bmatrix} \\ &= A_v + H_o P_o H_o^T + H_c P_c H_c^T \end{aligned} \tag{9}$$

where $G = \begin{bmatrix} H_o & H_c \end{bmatrix}_{M\times4}$.

Then, the UDRE is computed as follows:

$$\begin{aligned} \sigma_{UDRE}^2 &= \frac{1}{M} tr(P_{UDRE}) \\ &= \frac{1}{M}\left(tr(R) + tr(H_o \tilde{P}_o H_o^T) + tr(H_c \tilde{P}_c H_c^T)\right) \end{aligned} \tag{10}$$

where *tr*( ) is the trace of ( ).

$$V_{UDRE} = \kappa(P_{HMI}) \cdot \sigma_{UDRE} \tag{11}$$

where $K(P_{HMI}) = Q^{-1}(1 - P_{HMI}/2)$, and Q is the cumulative distribution function of a Gaussian random variable with zero mean and unit variance. In this paper, P_{HMI} =99.9% and $K(P_{HMI})$ =3.29.

B. SSDOP Definition

Geometric Dilution of Precision (GDOP) is used to describe the general relationship between the errors in the pseudorange measurements by the user to the user position accuracy [3]. Basing on GDOP, a concept of SSDOP is used to reflect the effect of changing the reference stations distribution on the accuracy of satellite ephemeris and clock estimates [6], then the expression of SSDOP is as follow:

$$\begin{aligned} V_{SSDOP} &= \frac{\sigma_{\Delta X}}{\sigma_{\Delta\rho}} = \frac{\sqrt{tr(\hat{P})}}{\sigma} = \frac{\sqrt{tr(P_o) + tr(P_c)}}{\sigma} \\ &= \sqrt{2tr\left[(H_{os}^T H_{os})^{-1}\right] + \left[H_c^T \left(2H_o \left(H_{os}^T H_{os}\right)^{-1} H_o^T + I\right)^{-1} H_c \right]^{-1}} \end{aligned} \tag{12}$$

C. Impact of SSDOP on UDRE

To establish the relationship between UDRE and SSDOP, (10) is changed into the following inequality.

$$\begin{aligned} \sigma_{UDRE}^2 &= \frac{1}{M}\left(M\sigma^2 + tr(H_o P_o H_o^T) + MP_c\right) \\ &< \frac{1}{M}\left(M\sigma^2 + tr(H_o^T H_o) tr(P_o) + MP_c\right) \\ &= \sigma^2 + tr(\hat{P}) \end{aligned} \tag{13}$$

Derived from (11), (12) and (12), an inequality is given as follow:

$$V_{UDRE} < 3.29\sigma\sqrt{1 + V_{SSDOP}^2} \tag{14}$$

Define α as restriction factor and its expression is as below:

$$\alpha = \frac{V_{UDRE}}{3.29\sigma\sqrt{1 + V_{SSDOP}^2}} \tag{15}$$

where $0 < \alpha < 1$.

Then, an equation about the UDRE and SSDOP is derived from (14) and (15).

$$V_{UDRE} = \alpha \bullet 3.29\sigma\sqrt{1 + V_{SSDOP}^2} \tag{16}$$

From (16), it is obvious that the value of UDRE is influenced by α and SSDOP when σ is a certain value. In order to express UDRE with SSDOP, the first thing is to find the factors that influence α.

Equation (15) is used to analysis the α with MATLAB®. The simulation environment is as : a) simulation duration: 86400 seconds; b) simulation interval: 3 seconds; c) the number and the type of the satellite: 5 geostationary satellites (GEO), 3 inclined geosynchronous satellites (IGSO) and these IGSOs have the same nadir track, and 24 medium earth orbiting satellites (MEO); d) mask angle of the reference station: 15°; e) the number of reference stations: 11, 27 and 36.

Fig. 2 shows that under different distribution of the reference stations, the curves of α of IGSO3 are piled one atop others during the time the IGSO3 are observed by the reference stations. It is deduced that the change of α is independent on the distribution of the reference stations.

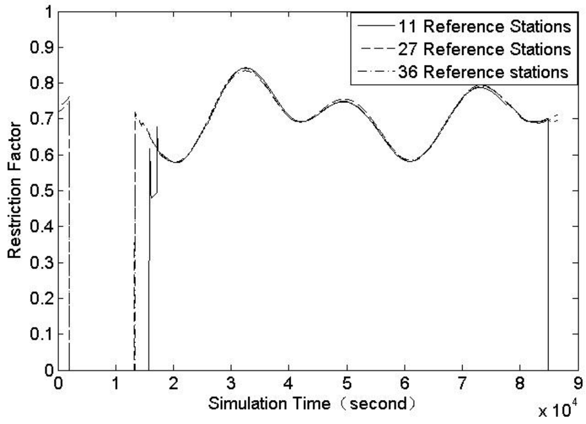

Figure 2. The curves of IGSO3's α under different reference stations distribution

Fig.3 shows that the curve of three IGSOs' α under 27 reference stations. Although these three IGSOs have the same nadir track, they have different orbit parameters which make them to enter into the same orbit at different time, 71000s, 42000s and 13000s, respectively. When the IGSOs enter into the same orbit, the change of α shows the same trend. However, when the IGSO moves into different area, the α is quite different. It is concluded that the change of α is influenced by the latitude and longitude of the satellite footprint.

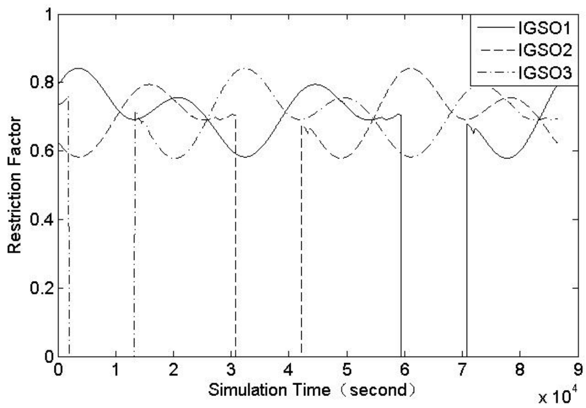

Figure 3. The curve of three IGSOs' α under 27 reference stations

Fig. 4 shows the curve of α changing with altitude in the geodetic coordinate. It is obvious that α is not influenced by the satellite altitude but only the longitude and latitude.

After analyzing the MEOs and GEOs, the same conclusion is got. The α is independent on the distribution of reference stations, SSDOP and the altitude of the satellite, just influenced by the longitude and latitude of the satellite footprint in the geodetic coordinate. Thus, the α can be written as

$$\alpha = f(\lambda, \varphi) \tag{17}$$

where λ and φ are the longitude and latitude of the satellite footprint in the geodetic coordinate, respectively.

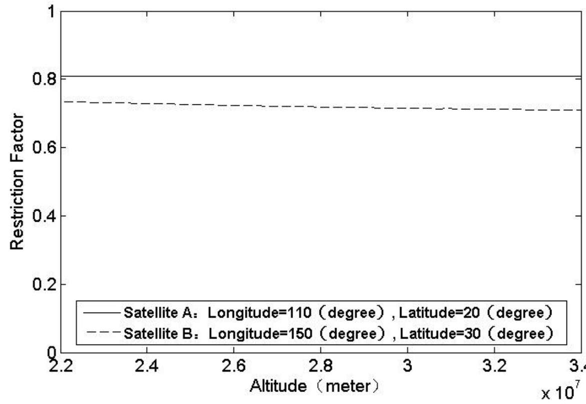

Figure 4. The curve of α changing with altitude under geodetic coordinate

Thus, (16)can be expressed as

$$V_{UDRE} = f(\lambda, \varphi) \bullet 3.29\sigma\sqrt{1+V_{SSDOP}^2} \tag{18}$$

From the equation, a linear trend is showed, or put it another way, the more SSDOP decreases, the smaller UDRE will become.

III. PPSO ALGORITHM

A. StationDistribution Using PSO

The PSO technique proposed by Eberhart and Kennedy [7] has been widely used in finding solutions for optimization problems. A swarm maintains several particles (each represents a solution) and simulates the behavior of bird flocking to find the final solutions. Each particle has a position vector ($X_i(t)$), a velocity vector ($V_i(t)$), the position at which the best fitness encountered by the particle ($lBest_i$), and the position of the best particle in the swarm (*gBest*).

In each iteration, the velocity of each particle is updated to their best encountered position and the best position encountered by any particle using the equation followed.

$$V_i(t) = \omega \cdot V_i(t-1) + c_1 \times r_1(t) \times (lBest_i - X_i(t-1)) + c_2 \times r_2(t) \times (gBest - X_i(t-1)) \tag{19}$$

where $V_i(t)$ is the velocity vector of the i^{th} particle at the t^{th} iteration; ω is called inertia weight; c_1 and c_2 are the acceleration coefficients called cognitive and social parameter respectively; $r_1(t)$ and $r_2(t)$ are random values, uniformly distributed between zero and one. The value of $r_1(t)$ and $r_2(t)$ is not the same for every iteration.

The position of each particle updates in every iteration. This is done by adding the velocity vector to the position vector, as below:

$$X_i(t) = X_i(t-1) + V_i(t) \tag{20}$$

where $X_i(t)$ is the position vector of the i^{th} particle at the t^{th} iteration.

Shi and Eberhart [8] have found a significant improvement in the performance of PSO with the linearly decreasing inertia weight over the iterations, time-varying inertia weight which is given in (21).

$$\omega = 0.4 + 0.5\left(\frac{MaxIteration - t}{MaxIteration}\right) \tag{21}$$

Then, Ratnaweera and Halgamuge [9] introduced a time-varying acceleration coefficient, which reduced the cognitive component, c_1, from 2.5 to 0.5 and increased the social component, c_2, form 0.5 to 2.5. This method is given as follows:

$$c_1 = 0.5 + 2\left(\frac{MaxIteration - t}{MaxIteration}\right) \tag{22}$$

$$c_2 = 2.5 - 2\left(\frac{MaxIteration - t}{MaxIteration}\right) \tag{23}$$

Using PSO to optimize reference stations distribution, the most important thing is to choose fitness function. UDRE is affected by the distribution of reference stations, so the average UDRE value of satellites will be the best candidate. If average UDRE is chosen, satellite ephemeris and clock corrections and variances need to be calculated in each iteration. It will seriously affect the searching speed. According to earlier analysis, SSDOP and UDRE have the linear trend, and the calculation of SSDOP is much easier than UDRE, which only needs the unite vectors from the reference stations to the satellite. Thus, the average SSDOP of satellites is chosen as the fitness function in the PSO [10]. The expression of fitness function is as follow:

$$f(X_i) = \frac{1}{K}\sum_{j=1}^{K} V_{SSDOP_j} \tag{24}$$

where K is the number of satellites, and V_{SSDOP_j} is the SSDOP of the j^{th} satellite.

The proposed PSO algorithm for distribution of reference stations is as below:

1) Set the maximum iterations as MaxIteration; randomly generate a group of particles and an initial velocity for every particle, each particle represents a distribution of reference stations. (Location of station may be two dimensional or three dimensional, according to the problem to be solved.)

2) Calculate fitness value of each particle using (24).

3) Set current particle as the new lBest if the fitness value of the current particle is smaller than the lBest's fitness value, *and set the minimum value among all lBests and gBest as gBest.*

4) Update the velocity and position of each particle using lBest and gBest by (19), (20), (21) ,(22) and (23).

5) Repeat Step 2 to 4 until the termination condition is met.

If the difference between the *gBest* and the last *gBest* is less than 0.001, the termination condition is met. When the termination condition is achieved, the final *gBest* is the best distribution of reference stations.

B. Station Distribution Using PPSO

There is a shortcoming of the proposed PSO algorithm for the reference station distribution. Sometimes, the proposed algorithm may converge too fast which makes the optimizing result to become the local optimization. Through 1000 runs Monte-Carlo simulation results, the probability of the proposed PSO algorithm falling in local optimization is 19% which is quite big.

In order to solve this problem, parallel computing is necessary. Parallel computing is a form of computation in which many calculations are carried out simultaneously, [11] operating on the principle that large problems can often be divided into smaller ones, which are then solved concurrently ("in parallel"). There are several different forms of parallel computing: bit-level, instruction level, data, and task parallelism. Parallelism has been employed for many years, mainly in high-performance computing. As power consumption (and consequently heat generation) by computers has become a concern in recent years, parallel computing has become the dominant paradigm in computer architecture, mainly in the form of multi-core processors. [12]

Parallel computers can be roughly classified according to the level at which the hardware supports parallelism—with multi-core and multi-processor computers having multiple processing elements within a single machine, while clusters and grids use multiple computers to work on the same task. Specialized parallel computer architectures are sometimes used alongside traditional processors, for accelerating specific tasks.

Here, the proposed PSO algorithm for optimizing distribution of reference stations is treated as task parallelism with multi-core and multi-processor computers, and the probability of all the parallel tasks fall in local optimization is quite low (0.02476% with five parallel tasks). Thus, parallel computing with several PSO algorithms will deduce the probability of the appearance of local optimization which happens easily when the proposed PSO algorithm is used.

The flow chart of PPSO for optimizing reference stations distribution is shown in Figure 4.

When all the threads are finished, the final *gBest* is the best distribution of reference stations.

IV. SIMULATION RESULTS

Experiments are made to compare the performance of the proposed PSO algorithm, the proposed PPSO algorithm, "*N*-Angled" method (NA) [4] and Exhaustive Grid Search method (EGS) by using MATLAB® with a multi-processor computer.

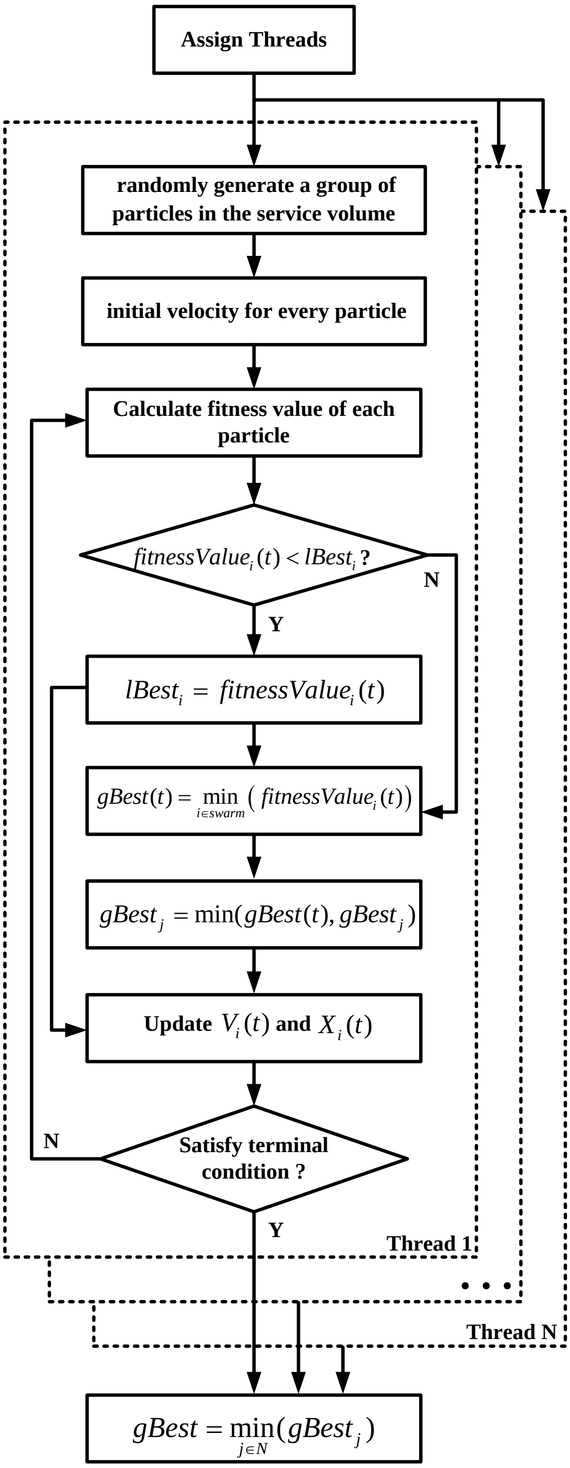

Figure 4. The flow chart of PPSO

A. Compare the Performance of PSO, NA and EGS

Using NA, there is a need to choose a stationary satellite. The best distribution of N reference stations is putting the N reference stations on the vertex of the polygon beneath the satellite. In the experiment, a GEO 70E is chosen. The optimal solution of four reference stations is shown in Fig.5.

From Fig.5, when a GEO is chosen and a searching area is regular, the performance of the three methods is the same. Analyzing the NA method, it is found that this method is not suitable for optimizing stations distribution when moveable satellites and irregular area are considered.

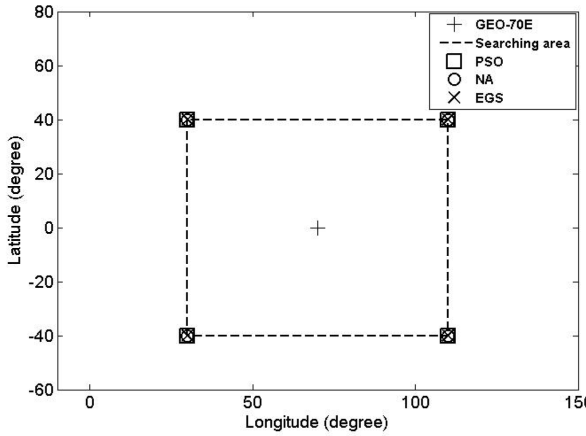

Figure 5. Performance of PSO, NA and EGS

Table I and Fig. 6 give the comparisons of PSO and EGS performance searching for the optimal solution of 4 reference stations in mainland of China with two dozens of movable satellites. The execution time of the algorithm is influenced not only by the capability of the algorithm but also by the hardware of the computer. Thus, the hardware of the computer used in the experiments are Intel Pentium Dual CPU 2.00GHz and memory bank 2.00GB.

TABLE I.
FITNESS VALUE AND EXECUTION TIME OF PSO AND EGS

	Fitness Value	Execution Time
PSO	347.80	99.20s
EGS stepped by 4-degree	387.39	6071.96s
EGS stepped by 5-degree	431.80	966.48s

Specifically, in Table I, the execution time of EGS stepped by 4-degree, the slowest, is 6071.96 seconds, and the fitness value also is not the best; the execution time of EGS stepped by 5-degree, 966.48 seconds, is much less than that of EGS stepped by 4-degree, its fitness value, however, is the worst. The reason for this is that EGS's performance depends on the grid division step of the service area. The smaller step becomes, the better performance will be. But the computation time will increase exponentially. Finally, it is becoming a NP-hard problem. On the other hand, not only is the fitness value of PSO smaller than the EGS, but also the execution time is 1/60 times that of EGS stepped by 4-degree.

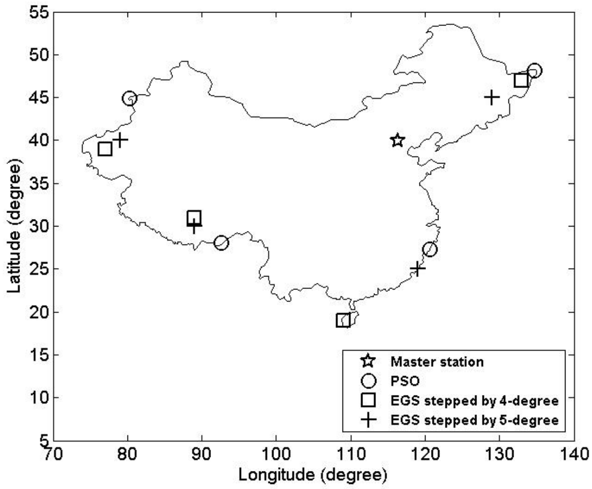

Figure 6. Performance of PSO and EGS in mainland of China

In the Fig. 6, the stations found by PSO are all on the border, but those found by EGS are just near the border. That's because EGS is dependent on the grid division and can't scout the entire solution space exhaustively. However, PSO searches the solution space dynamically. Therefore, the distribution of reference stations found by PSO is better than that found by EGS.

B. Compare the Performance of PPSO and PSO

Due to parallel computing programs are more difficult to write than sequential ones, Parallel Computing Toolbox™ which is an easy use toolbox in MATLAB® is used to simulate PPSO with five parallel tasks.

The simulation results are shown in Table II and Fig. 7. Comparing the performance of the PPSO and PSO algorithm which is given in Fig. 7, the result found by PSO falling in local optimization is not as good as expected. This distribution will have worse influence on the geometry of the satellite when the satellite is on the east of China. Thus, it will affect the quality of UDRE estimation. The optimization distribution found by PSO and PPSO are quite similar. Due to the PPSO algorithm is based on PSO and the PSO algorithm is optimizing result in the solution space dynamically, the results found by PPSO and PSO are not the same.

In Table II, the PSO (local optimization) converging too fast has the smallest execution time, 58.56 seconds, and its fitness value is twice that of PPSO. This means that the UDRE calculated using the reference station found by PSO falling in local optimization will be twice that of PPSO. If this conservative UDRE is used by the users in the service volume will reduce the availability of SBAS and safety of the users. The fitness value of PPSO is the best, 337.53, and its execution time is bearable, 1.5 times that of PSO. The most important thing is that the proposed PPSO algorithm can avoid converging too fast (as mentioned above, the probability of PPSO falling in local optimization with five parallel tasks is 0.02476%) which can be met by PSO.

TABLE II.
FITNESS VALUE AND EXECUTION TIME OF PPSO AND PSO

	Fitness Value	Execution Time
PPSO	337.53	141.19s
PSO (Local optimization)	694.71	58.56s
PSO	347.80	99.20s

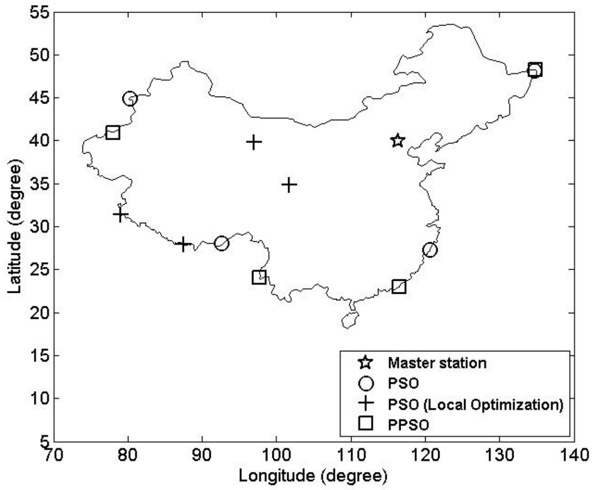

Figure 7. Performance of PPSO and PSO in mainland of China

V. CONCLUSIONS

By analyzing the expressions of SSDOP and UDRE, a linear trend is found. The proposed PSO algorithm uses average SSDOP as the fitness function to find optimal reference stations distribution in searching area, but this method, sometimes, may fall in local optimization. Thus, a PPSO algorithm is proposed to solve this problem. Then, Experiments are made to compare the performance of the proposed PPSO algorithm, the proposed PSO algorithm, NA and EGS. After analyzing the results, it is found that the proposed PPSO algorithm outperforms the other methods, and isn't restricted by the state and number of the satellites and the outline of the searching area. The most important thing is that the proposed PPSO algorithm can avoid falling in local optimization.So, the proposed PPSO algorithm can help find good reference stations distribution in SBAS, and increase the accuracy of UDRE , enhance the availability of SBAS and enhance the integrity and safety of flight.

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