A type of collective detection scheme with improved pigeon-inspired optimization

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Abstract

Purpose – With increasing demand of localization service in challenging environments where Global Navigation Satellite Systems (GNSS) signals are considerably weak, a powerful approach, the collective detection (CD), has been developed. However, traditional CD techniques are computationally intense due to the large clock bias search space. Therefore, the purpose of this paper is to develop a new scheme of CD with less computational burden, in order to accelerate the detection and location process.

Design/methodology/approach – This paper proposes a new scheme of CD. It reformulates the problem of GNSS signal detection as an optimization problem, and solves it with the aid of an improved Pigeon-Inspired Optimization (PIO). With the improved PIO algorithm adopted, the positioning algorithm arrives to evaluate only a part of the points in the search space, avoiding the problems of grid-search method which is universally adopted.

Findings – Faced with the complex optimization problem, the improved PIO algorithm proves to have good performance. In the acquisition of simulated and real signals, the proposed scheme of CD with the improved PIO algorithm also have better efficiency, precision and stability than traditional CD algorithm. Besides, the improved PIO algorithm also proves to be a better candidate to be integrated into the proposed scheme than particle swarm optimization, differential evolution and PIO.

Originality/value – The novelty associated with this paper is the proposition of the new scheme of CD and the improvement of PIO algorithm. Thus, this paper introduces another possibility to ameliorate the traditional CD.

Keywords GNSS, Collective detection, GNSS signal acquisition, Pigeon-inspired optimization, Weak signal acquisition

Paper type Research paper

1. Introduction

Global Navigation Satellite Systems (GNSS) are systems which provide positioning services based on the signals received from a constellation of satellites. More specifically, systems like GPS, Beidou, Glonass, Galileo are all based on this concept. With the same principle that users obtain their locations from the measured distance or distances between them and in-view satellites, these systems provide users with the location service (Closas *et al.*, 2007). The distances measured by estimated propagation time of signals from in-view satellites to receivers, acquisition of GPS signals forms the basis of positioning. Recent years, the increasing demand of indoor and harsh environment location services creates significant challenges to the traditional acquisition techniques, namely, serial search acquisition and parallel search acquisition (Borre *et al.*, 2007; Grewal *et al.*, 2007; Tsui, 2000). As they can no longer detect the correlation peak of signals in these scenario where GNSS signals are 10-25 dB weaker (Dedes and Dempster, 2005). Thus, acquisition of weak signals comes to attract the attention of researchers and various methods have been proposed.

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Varied as the methods are, they are mainly based on two principles: helping the receivers with additional information and increasing the sensitivity of receivers. Based on the first principle, the concept assisted-GNSS which takes advantage of information received from base stations (BSs) or mobile stations (Van, 2009) has been introduced and utilized, while another concept High Sensitivity GNSS acquisition, where the coherent integration time or non-coherent integration time is increased (Ziedan and Garrison, 2004), comes from the second. Recently, a third approach, based on the combination of these two principles, named collective detection (CD) which combines signals from different satellites has been proposed and begins to attract more and more attention of researchers for its high performance in weak signal detection (Li *et al.*, 2014).

By this method, positioning service can be provided with signals whose carrier to noise ratios (C/N_0) is 20 dB (Cheong, 2011). However, new challenges are raised by its high computational load mostly due to the clock bias search range which is $\pm$ 150 km. With this clock bias range and $\pm$3 km, $\pm$3 km, $\pm$600 m for the search ranges in north, east and down directions, the number of points to evaluate reaches nearly 31 million (Axelrad *et al.*, 2011). To solve this problem, various approaches have been proposed.

Together with the proposition of original CD, the idea to conduct the acquisition by several iterations with refined search spacings is proposed by Axelrad *et al.* (2011). They also propose to utilize an averaged correlogram at the beginning of the search to accelerate it. This idea of multi-resolution is also adopted by Omar *et al.* (2014) and Li *et al.* (2014). However, instead of using an averaged correlogram, Li *et al.* propose to use small clock bias spacing with large horizontal position step size to reduce computational burden and obtain high time resolution at the same time, while Omar *et al.* integrate this idea into the choice of sampling frequency before calculation of correlation values. In Omar *et al.* (2014), although the proposed method is proved to have higher efficiency compared to the traditional CD, its sensitivity decreases after several iterations. A hybridization of CD and conventional detection is proposed by Cheong *et al.* (2011a). Conducting Singular Value Decomposition on the direction cosine matrix with the successful detected channels by conventional detection, they reduce the solution space to a sub-space on which the CD is performed, thus to reduce computational load. Narula *et al.* (2014) proposes to roughly estimate the clock bias from the difference of a geometric code-phase and a measured code-phase by a strong satellite signal, reducing clock bias search range from 300 km to 100 m. This method is based on the hypothesis that there is at least one strong satellite signal, and that we know which one it is. Similar idea has already been proposed by Esteves (2014a) a bit earlier. But instead of clock bias, the distance between the receiver and BS is estimated. Other than focussing on the idea of multi-resolution, a new representation of horizontal position search space is proposed by Esteves (2014a) and Esteves *et al.* (2014b). Instead of a representation in Cartesian coordinates, polar coordinates are utilized, which decreases considerably the total number of points evaluated, and relatively good results are obtained. Although the third dimension is neglected, there would not be much influence as the scenario is in urban areas.

All the approaches proposed above view the acquisition as a detection problem. Yet another possibility is to consider it as an estimation problem (Esteves, 2014a). Based on this idea, Closas *et al.* (2007) adopts Maximum Likelihood Estimation by solving an optimization problem with sequential Monte Carlo methods, to realize positioning. In the process of estimation, signals from different satellites are combined. This is another perspective of CD or collective acquisition, which is also adopted by Cheong (2011) where the SAGE optimization algorithm is introduced to solve optimization problems. As stated by Closas *et al.*, more computationally efficient optimization algorithms need

to be developed based on this view. Fortunately, research on it has also progressed (Zhang *et al.*, 2008).

Apart from the theoretical improvements above, an efficient implementation of CD in Matlab has been discussed by Cheong *et al.* (2011b). They propose an efficient pre-processing method which significantly reduces the overall computation.

As can be seen, in traditional CD and the variants above as well, for each user, we search the whole search space of the variable vector Vec with certain, or variable, step sizes. The large span of clock bias search space results in heavy computational load searching the whole space with a relatively fine resolution. To accelerate the search, most of the previous work focusses on varying the search steps (Axelrad *et al.*, 2011; Li *et al.*, 2014; Omar *et al.*, 2014). However, nobody, to the author's knowledge, has considered the acquisition problem as an optimization problem. In fact, by adopting the Swarm Intelligence (SI) algorithm, we can obtain the user's relative position vector with good resolutions without searching the whole search space.

Based on this idea, in this paper, a new CD scheme based on an improved Pigeon-Inspired Optimization (PIO) algorithm is proposed. Simulated signal-based experiments have been conducted to test its performance. According to the experimental results, the proposed scheme generally outperforms the traditional CD in terms of efficiency, accuracy and stability. The execution time is divided at least by 4 compared to the traditional CD, with the roughly the same or even better precision. Particle swarm optimization (PSO) differential evolution (DE) and PIO are also integrated into the new CD scheme to acquire simulated GNSS signals but proves to perform worse than the improved PIO. Acquisitions of real GNSS signals in hash environments have also been carried out. As the results suggest, with almost the same accuracy (in terms of order of magnitude), the proposed scheme is much more efficient than the traditional CD.

The rest of this paper is organized as following. In Section 2, the principle of CD is introduced. Then, the optimization problem formulation of acquisition is proposed in Section 3, where the new scheme is also introduced. Section 4 concerns the introduction of PIO algorithm, while in Section 5 the Expand and Contract Pigeon-Inspired Optimization (ECPIO) algorithm is presented. Experimental results and analysis are provided in Section 6, and finally, conclusions are drawn in Section 7 with future research directions outlined.

2. CD

Instead of processing signals from different satellites individually, CD processes them collectively, combining correlation values of individual satellites. Thus, acquisition of weak signals can benefit from the presence of strong signals in the vector, which is the core idea of CD (Esteves *et al.*, 2014b). Different from conventional methods, instead of searching in code delay-Doppler frequency space, CD searches in the space of receiver position relative to the position of BS (assistance information), and clock bias. Thus, the variable vector to obtain is defined as $X=[\Delta N, \Delta E, \Delta D, \Delta b]$ where the first three dimensions represent, respectively, the algebraic distances between the receiver and the BS in north, east and down directions. The fourth dimension denotes the relative clock bias of receiver to the BS. Thus, the pseudorange of receiver ρ_{rk} is given by Equations (1) and (2) based on the pseudorange of BS, denoted as ρ_k, measured by satellite k:

$$\Delta\rho_k = -\cos(az_k)\cos(el_k)\Delta N - \sin(az_k)\cos(el_k)\Delta E + \sin(el_k)\Delta D + c\cdot\Delta b \tag{1}$$

$$\rho_{rk} = \rho_k + \Delta\rho_k \tag{2}$$

The az_k and el_k represent, respectively, the azimuth angle and elevation angle of satellite k. For the sake of simplicity, the rest of this work is based on the hypothesis below:

H1. In the process of acquisition of simulated signals, the carrier in the received signal is supposed to be already eliminated.

Under this assumption, the detection metric of CD can be calculated by (Esteves, 2014a):

$$D_{\text{collective}}(\Delta N, \Delta E, \Delta D, \Delta b) = \sum_k \left|S(\tau_k)\right|^2 \tag{3}$$

where $S(\tau_k)$ denotes the correlation value of the received signal and the signal generated for satellite k at the code-phase τ_k obtained by:

$$\tau_k = \frac{\text{mod}\left(\rho_{rk}, c \cdot T_{\text{code}}\right)}{c \cdot T_{\text{code}}} \cdot N_{\text{code}}. \tag{4}$$

T_{code} denotes the code period and N_{code} represents the number of code chips per period (Esteves, 2014a). If this metric surpasses a pre-defined threshold, the signal could be detected. Once the signal detected, the corresponding code-phase and Doppler shift can be obtained using the method in (Closas *et al.*, 2007). The flow chart of the traditional CD is shown in Figure 1.

3. Problem formulation and characteristics investigation

3.1 Problem formulation and the proposed scheme

As described in Section 2, the CD problem can be defined as searching for the variable vector $X = [\Delta N, \Delta E, \Delta D, \Delta b]$ in such as that the detection metric calculated by Equation (3) surpasses the pre-defined threshold. As the metric is always positive, which can be seen from Equation (3), it is obvious that if the maximum of the detection metrics for all of the possible vectors in the search range surpasses the threshold, the signal is detected. Therefore, the acquisition problem can be formulated as an optimization problem, or maximization problem, described as follows:

Formulation 3.1. An acquisition-related optimization problem is to search for the optimal vector X in the search space (in meter):

$$\begin{aligned} \Delta N &\in [-100{,}00, 100{,}00] \\ \Delta E &\in [-100{,}00, 100{,}00] \\ \Delta D &\in [-200, 200] \\ \Delta b &\in [-150{,}000, 150{,}000], \end{aligned} \tag{5}$$

which maximizes the criterion function:

$$\begin{aligned} J &= \text{fun}(D_{\text{collective}}(\Delta N, \Delta E, \Delta D, \Delta b)) \\ &= \text{fun}\left(\sum_k \left|S(\tau_k)\right|^2\right) \end{aligned} \tag{6}$$

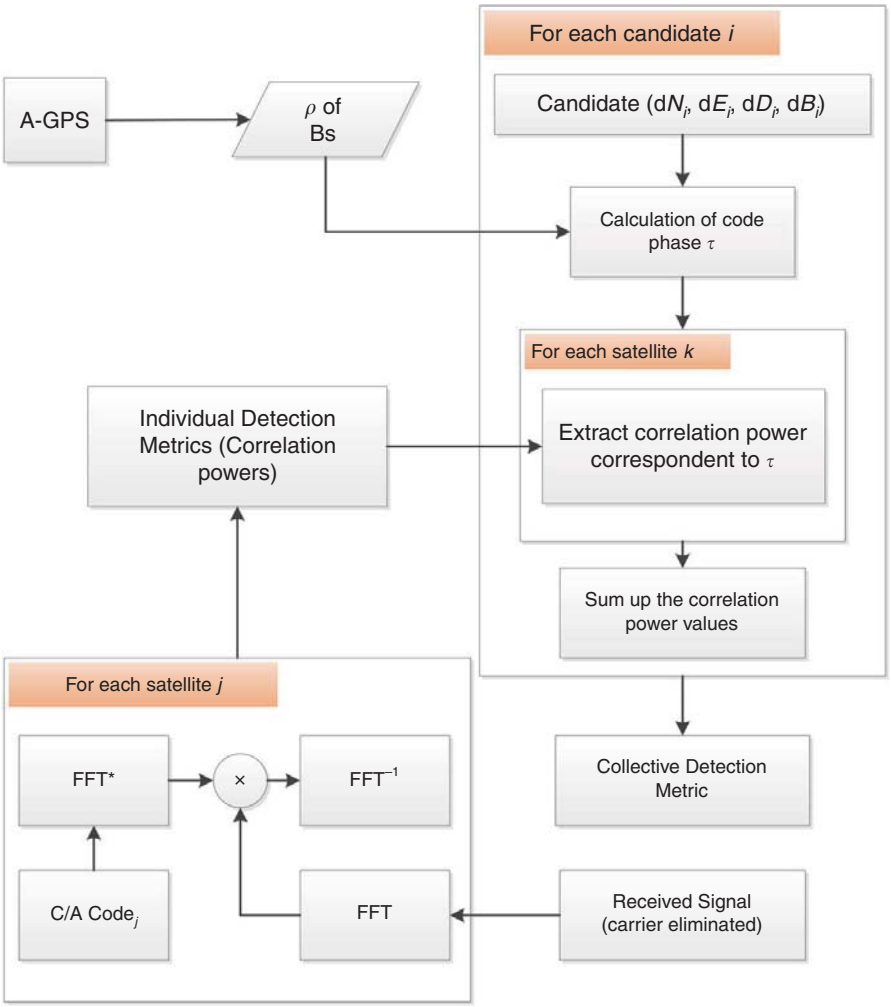


Figure 1. Flow chart of traditional CD

where fun(x) is an increasing function. Then the decision of detection is made with the surpass of a threshold determined by a pre-defined false-alarm probability.

In the case of this work, the function fun(x) is the identity function. Besides, the criterion function used in the proposed algorithm is $-J$, changing the maximization problem into a minimization problem. Hence, based on this formulation, the proposed scheme is shown in Figure 2. Furthermore, to concentrate on our contribution, the hypothesis is proposed:

H2. In order to focus on the optimization problem formulated in 3.1, the detection decision process is neglected in our work. Thus, the acquisition problem is totally transformed into an optimization problem.

This hypothesis is reasonable, because only the search of the peak is improved in the traditional CD algorithm. As for the detection decision process, we can use the same.

3.2 Characteristics investigation

In order to solve the acquisition-related optimization problem defined above, its characteristics are investigated and the results are as follows.

First, the search range is considerably large, and different dimensions' search ranges differ a lot. For example, the search range of ΔD dimension is only 400 m, while

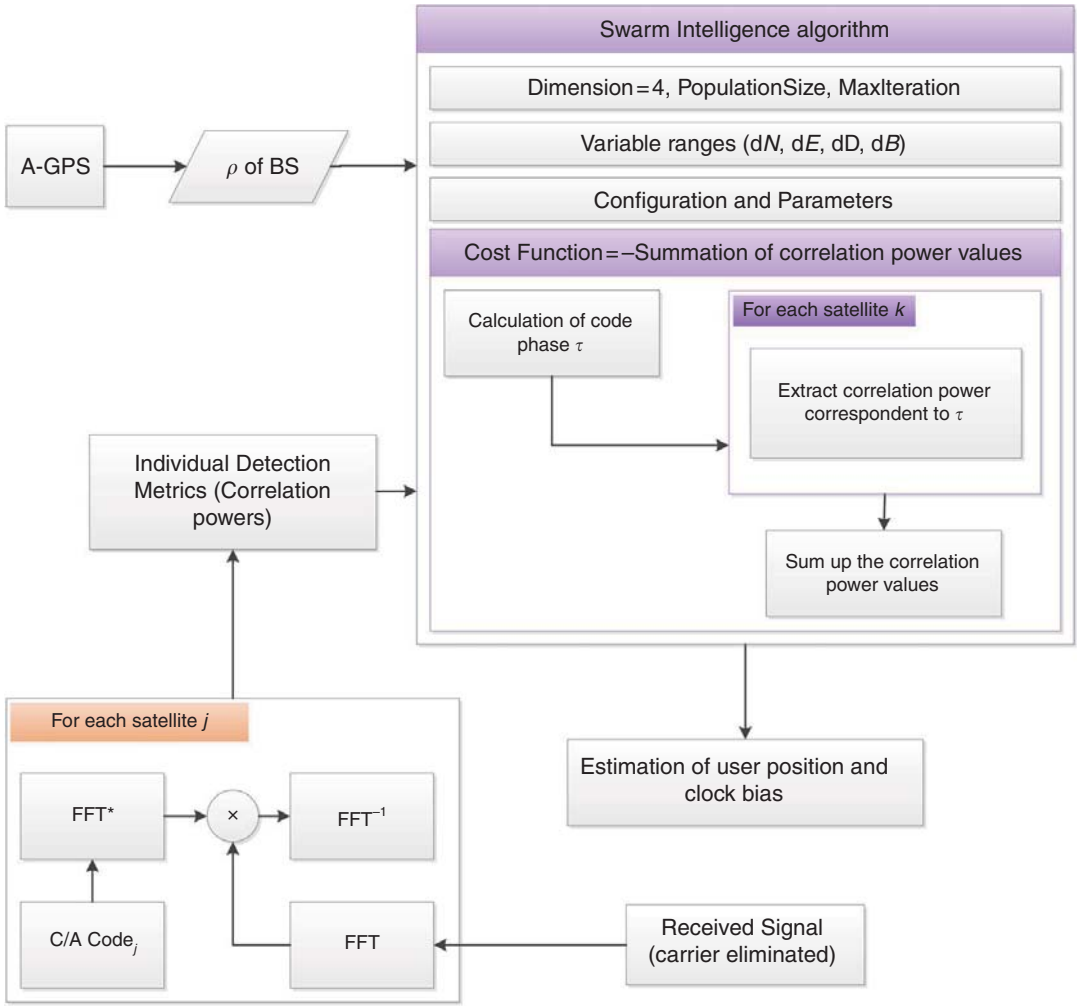
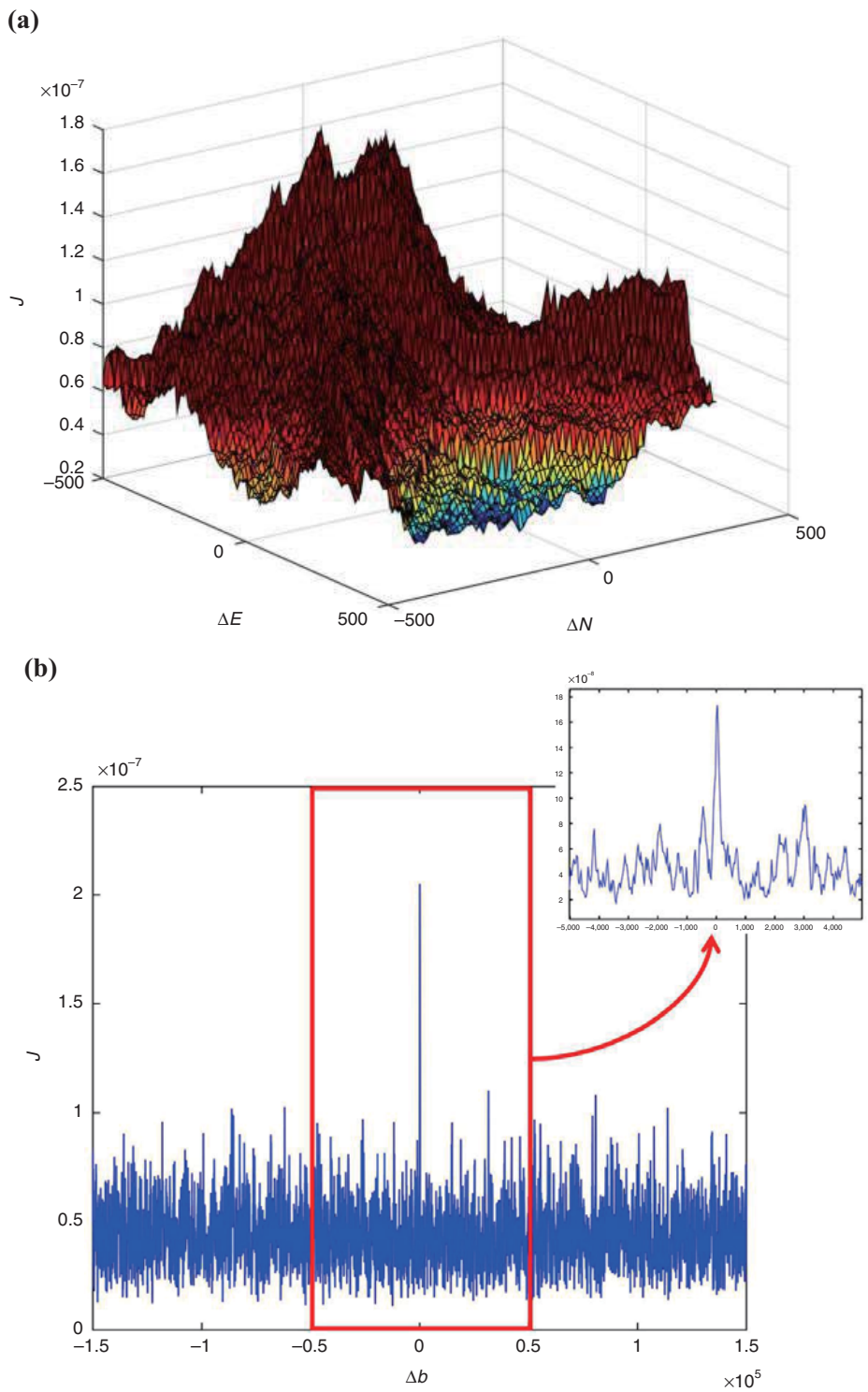


Figure 2.
Proposed structure of new CD

that of clock bias reaches 300 km. For traditional CD, the large clock bias search range is really a big challenge for its consumption of time, while for SI algorithm, the uneven search range may degrade its performance as well.

Second, the optimization problem formulated above is an intense multi-modal problem, which can be illustrated by the following results. First, we fix the ΔN, ΔE, ΔD at the exact value, and we calculate J for each possible Δb, with a certain spacing. Second, Δb and ΔD are fixed, while ΔN and ΔE vary. The results of the corresponding values of J are shown in Figure 3 (a) and (b). Both simulations are conducted in the case of a weak signal environment (35 dB). As we can see from the results, both the search in the ΔE, ΔN dimension and that in the Δb dimension have a considerable number of local optima. Therefore, in order to succeed in finding out the optimal position, forceful ability of jumping out of local optima is required. Besides, although in each of the figures a peak can be seen clearly, the difference of the peak value and the local optima is extremely slight (order of magnitude 10^{-7}). This characteristic doubles the difficulty created by the problem's multi-modal characteristic.

These observations of the characteristics of the criterion function guide the optimization algorithm choice and the modifications or improvements needed.



Notes: (a) J function of ΔE and ΔN; (b) J function of Δb

Figure 3. Characteristic investigation of acquisition-related optimization problem

3.3 Direct location probability

In this work, the notion of "direct location probability"(P_l) is introduced, which represents the probability that the user's position estimated directly by the search of highest correlation peak value is correct. As the vector to search contains four

components, by traditional search methods and CD alike, the user's position can be correctly calculated only if more than four measurements from, respectively, four satellites are acquired. Hence, we define the direct location probability as follows:

Definition 1. (Direct location probability) Consider N independent acquisitions. The direct location probability is defined by:

$$P_l = \frac{m}{N} \tag{7}$$

where m denotes the number of acquisitions with at least four correctly estimated code phases.

This criterion reflects the performance of the acquisition method from another aspect other than the mean estimation errors. Instead of a precision evaluation, this criterion evaluates the stability and reliability of an acquisition approach. With a higher P_l, the performance of algorithm is guaranteed with a higher stability.

4. PIO

As specified in the section above, the formulated optimization problem is an intense multi-modal problem where a great number of local optima exist. Faced with this kind of optimization problems, traditional optimization algorithms which are mostly single-point based, for example gradient decent algorithms, get easily trapped into local optima. Therefore, a new kind of population-based optimization algorithms named SI optimization algorithms (Kennedy *et al.*, 2001) has been invented and researched on.

SI algorithms get their inspiration from the swarm behaviors of natural creatures. PSO (Kennedy and Eberhart, 1995; Duan *et al.*, 2013), artificial bee colony (Luo and Duan, 2014), ant colony optimization (Geis and Middendorf, 2008; Van *et al.*, 2009), biogeography-based optimization (Ababneh, 2015; Duan and Deng, 2014) and differential evolution (DE)(Rainer and Kenneth, 1997) are all algorithms of this kind and have been applied to a wide range of problems. PIO algorithm, first proposed by Duan and Qiao (2014), is yet another novel SI algorithm. Motivated by the homing mechanism of pigeons, two operators named map and compass and landmark are abstracted consisting the main frame of the PIO algorithm. Since its proposition, PIO has proven itself as a worthy competitor to existing algorithms in various applications (Duan and Qiao, 2014; Li and Duan, 2014a, b; Zhang and Duan, 2015) and has begun to attract more attention for its efficiency and simplicity.

As is the case for other SI algorithms, the PIO algorithm starts with the initialization of the population. Each individual is initialized with a random position in the search space denoted as $\overrightarrow{X}_i = [x_{i1}, \ldots, x_{iD}]$ and a random flying velocity $\overrightarrow{V}_i = [v_{i1}, \ldots, v_{iD}]$ where $i = 1, \ldots, N_c$. N_c and D represent the population size and problem dimension, respectively. Then comes the two-stage optimization process as described below.

4.1 Far away stage

In this stage, the whole population is far from the destination and the map and compass operator is utilized to guide the pigeons near to the destination. During this stage, the guidance provided by the map and compass leads the pigeons by:

$$\overrightarrow{V}_i(t) = \overrightarrow{V}_i(t-1) \cdot e^{-Rt} + \text{rand} \cdot \left(\overrightarrow{X}_g - \overrightarrow{X}_i(t-1)\right) \tag{8}$$

$$\vec{X}_i(t) = \vec{X}_i(t-1) + \vec{V}_i(t) \tag{9}$$

where R represents the map and compass factor (Duan and Qiao, 2014), $\vec{X}_g$ denotes the present global best position and rand is a randomly generated vector with each dimension in [0,1]. As can be seen from the equations, in this stage, the pigeons are guided by the current global best position with decreasing influence from its inertial velocity.

4.2 Near destination stage

When reaching this stage, the pigeons are already near the destination. Therefore, the landmark operator is activated and preferred. The pigeons are classified into two parts. Those that are familiar with the landmarks fly directly to the destination (Duan and Qiao, 2014):

$$\vec{X}_c(t-1) = \frac{\sum_{i=1}^{N_p(t-1)} \vec{X}_i(t-1) \cdot f\left(\vec{X}_i(t-1)\right)}{N_p(t-1) \cdot \sum_{i=1}^{N_p(t-1)} f\left(\vec{X}_i(t-1)\right)} \tag{10}$$

$$\vec{X}_i(t) = \vec{X}_i(t-1) + \text{rand} \cdot \left(\vec{X}_c(t-1) - \vec{X}_i(t-1)\right) \tag{11}$$

where N_p denotes the current population size and f represents the fitness function. Those that are not familiar with the landmarks follow the first part by applying (Duan and Qiao, 2014):

$$N_p(t) = \frac{N_p(t-1)}{2} \tag{12}$$

assuming that they follows perfectly their guides.

5. ECPIO

Simple and efficient as the PIO algorithm is, it still suffers from some drawbacks that degrade its performance. The most important one for our case is that provided its fast convergence, it still gets easily trapped into local optima. As the acquisition-related optimization problem is an intensely multi-modal optimization problem, in this section two modifications on the two stages, respectively, are introduced to improve the performance of PIO facing complex multi-modal problems.

5.1 Expand and contract flying

As can be seen from Equation (8), the influence of the inertial part decreases drastically as the pigeons advance due to the effect of the exponential function. Hence, after several iterations, Equations (8) and (9) can be approximated as:

$$\vec{X}_i(t) = \vec{X}_i(t-1) + \text{rand} \cdot \left(\vec{X}_g - \vec{X}_i(t-1)\right). \tag{13}$$

By this equation all the pigeons will fly directly to the current global best position and hence get stuck there, which prevents the progress of algorithm.

Therefore, in order to ameliorate this situation, an expand and contract flying strategy is proposed. In this strategy, when the pigeons think that the whole flock has been well informed of the current best path, they prefer to fly on their own, making the whole swarm expand while advancing. The criteria of this judgment is based on the population dispersion (D_p) defined as below.

Suppose N individuals (vectors) denoted as $\vec{X}, \ldots, \vec{X}_N$ of a population, the Population Dispersion, denoted as D_p, is defined as the variance of the individuals' distances to their mean position. Specifically, in each iteration:

$$\vec{X}_{\text{mean}} = \frac{1}{N}\sum_{i=1}^{N}\vec{X}_i \tag{14}$$

$$\text{Dis}_i = \left\|\vec{X}_i - \vec{X}_{\text{mean}}\right\|, \quad i \in 1, \ldots, N \tag{15}$$

$$D_p = \text{var}\left(\overrightarrow{\text{Dis}}\right) \tag{16}$$

where $\overrightarrow{\text{Dis}}$ is the distance vector and var the variance function.

This definition describes the spreading range of the pigeons. With this definition, the judgment criteria can be formulated as following:

Criteria 5.1. In each iteration of the first stage, if $D_p(t) < \text{coeff.}D_p(t-1)$, the map and compass factor will be set to R_1 ($R_1 < 0$, and its absolute value decreases as the pigeons advance), otherwise it will be set to R coeff. denotes a scaling factor in [0,1].

In the case of this work, R_1 is determined by $R_1 = -20/t$ where t denotes the current iteration index. Adopting this strategy, in the first stage, the pigeons will conduct an expand (when R_1 is adopted) and contract (when R is adopted) flying, which pulls the algorithm out when trapped. Besides, as coeff. $\in$[0,1], the whole swarm tends to converge to a certain degree despite its expansion behavior.

5.2 Slower following

As described in Section 4, the pigeons that are not familiar with the landmarks follow perfectly those that are by Equation (12). This operation can intensely accelerate the algorithm, however, it reduces the search power of the whole swarm. Therefore, in the proposed algorithm, the following of the followers is supposed to be slower and less precise by eliminating this operation. Moreover, Equation (10) is replaced with:

$$\vec{X}_c(t-1) = \frac{\sum_{i=1}^{N_p(t-1)}\vec{X}_i(t-1)\cdot f\left(\vec{X}_i(t-1)\right)}{0.8N_p(t-1)\cdot\sum_{i=1}^{N_p(t-1)} f\left(\vec{X}_i(t-1)\right)} \tag{17}$$

due to the simulation results. With these modifications, the flow chart of the proposed ECPIO algorithm is shown in Figure 4. This algorithm is to replace the SI algorithm in the proposed scheme shown in Figure 2.

6. Experimental results and analysis

For the purpose of investigating the performance of the newly proposed acquisition approach, three experiments are carried out. As the formulated problem is an intense

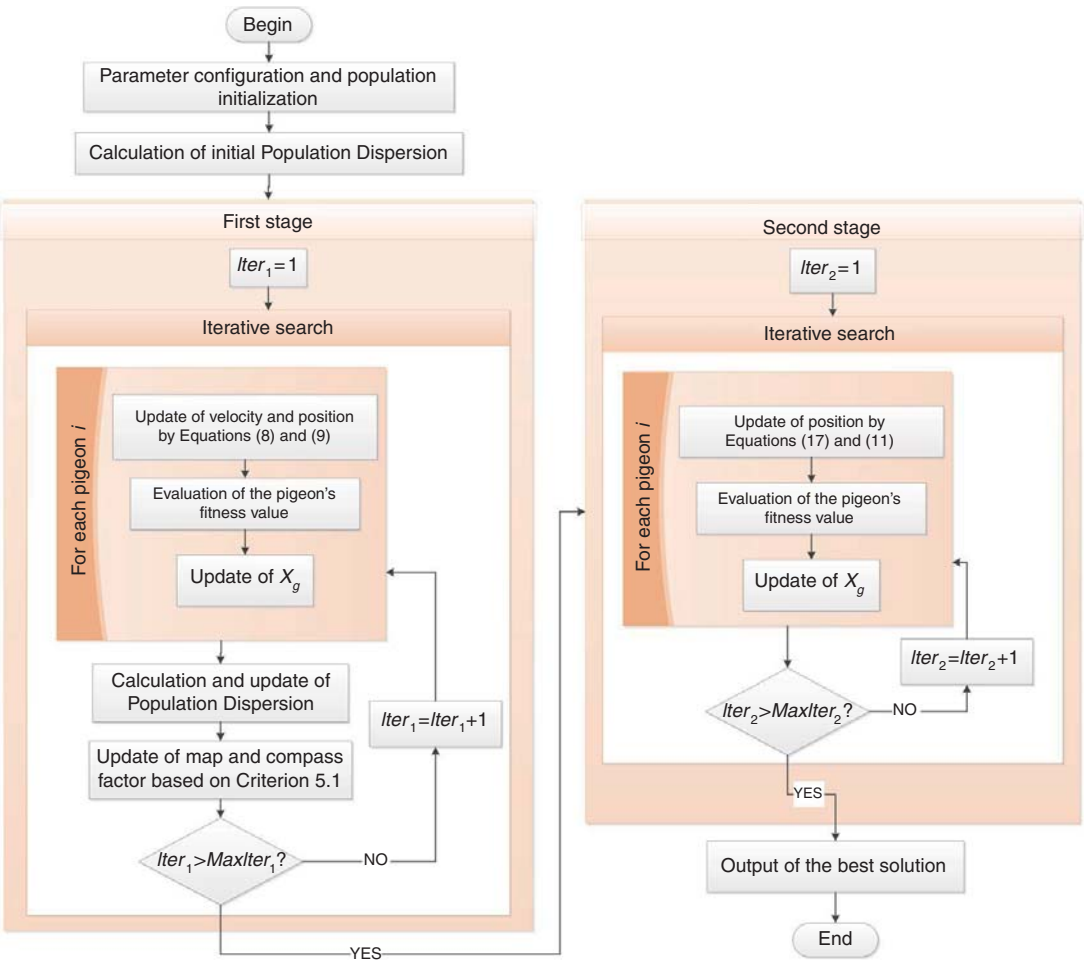


Figure 4. Flow chart of ECPIO algorithm

multi-modal problem, the proposed ECPIO is first tested on the minimization of rotated Rastrigin function, then applied to the acquisition of simulated GNSS signals, where the carrier is considered to be already eliminated as stated in *H1*. Finally, the proposed scheme with ECPIO is tested with real GNSS signals. In the first experiment, the performance of ECPIO is compared with PSO, DE and the Original PIO, while in the last two experiments, comparison between the CD with the proposed scheme and the traditional CD is conducted.

6.1 Function optimization test

In this experiment, the proposed ECPIO algorithm is tested on a ten-dimension rotated Rastringin function where the original variable is rotated by left multiplying an orthogonal matrix M to increase the complexity of the function by changing separable functions to nonseparable functions without influencing the shape of the functions. The algorithms are executed 10 times independently, and the results of ECPIO, PSO, DE, and PIO are compared. Parameter configuration of the four algorithms is given in Table I and the results are shown in Table II.

As can be seen from the results, faced with a complex multi-modal function, ECPIO generally outperformed the other three algorithm. Hence, ECPIO is a promising candidate for solving the formulated problem.

6.2 Simulated signal experiments

6.2.1 Experimental settings. In order to have the best constellation geometry, the Geometrical Dilution of Precision is set to be 1. The mask angle which is the minimum elevation angle of a visible satellite is set to be 10°, for in real situation all the 32 satellites are not always visible from the receiver. Under our circumstances, 10 satellites are visible (i.e. ten code phases to estimate). Although weak signals are included (32-40 dB), in pursuit of efficiency, both coherent and non-coherent integration time are fixed at 1 m s. The BS is in SUPAERO in Toulouse. Its position expressed in Earth-Centered-Earth-Fixed Cartesian coordinates and in geodetic coordinates (measured by the receiver shown in Figure 5 (a)) are shown in Table III. The true position of the receiver (relative to BS) is set to be (0,0,0,0) in the east-north-up coordinate system centered at BS. The last dimension corresponds to the receiver's clock bias.

The proposed scheme with ECPIO is utilized to solve the problem formulated in 3.1 with simulated signals. Its performance is compared to that of the proposed scheme with PSO, DE, PIO and that of traditional CD (version multi-iteration (Axelrad *et al.*, 2011). The parameter configuration is the same as in Table I except the changes below:

- for DE and PSO, $MaxIter = 1{,}800$
- for PIO, $MaxIter_1 = 700$ and $MaxIter_2 = 1{,}100$
- for ECPIO, $MaxIter_1 = 1{,}000$ and $MaxIter_2 = 800$

the number of acquisitions executed to acquire statistical characteristics is $RunTimes = 20$.

6.2.2 Comparison between traditional CD and CD with the proposed scheme (ECPIOCD). Experiment with signal of 35 dB. With the configuration accomplished, simulations are carried out. Direct location probability (P_l), the mean values of direct positioning bias error (MBE), direct positioning position error (MPE), execution time (ExT), number of points evaluated (NPE), and number of correctly estimated code phases (MCPh) of the two schemes (namely, traditional CD and ECPIOCD) are evaluated and compared. The results are shown in Table IV with the best marked in italic.

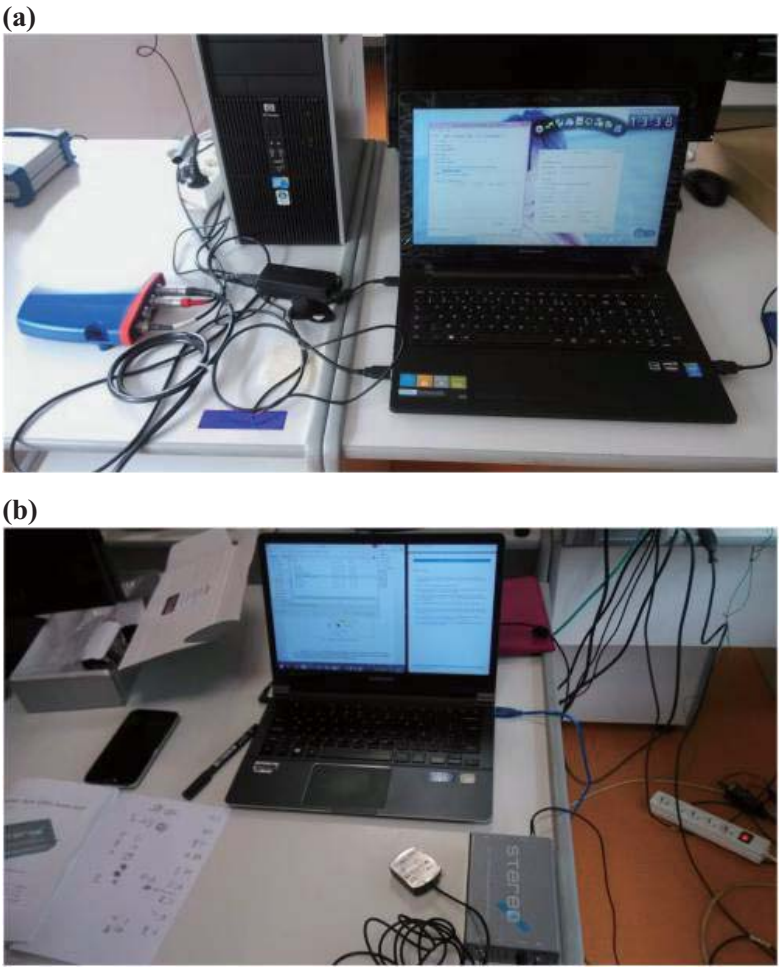
Table I. Parameter configuration

Algorithms	Parameters settings
PSO (Zhan *et al.*, 2011)	$\omega = 0.9 \sim 0.4$, $C_1 = C_2 = 2.0$, $V_{\max} = 0.2 \times \text{Range}$, $MaxIter = 1{,}000$
DE (Zhan *et al.*, 2012)	$F = 0.5$, $\text{CR} = 0.5$, $MaxIter = 1{,}000$
PIO (Duan and Qiao, 2014)[a]	$MaxIter_1 = 400$, $MaxIter_2 = 600$, $R = 0.2$
ECPIO	$MaxIter_1 = 850$, $MaxIter_2 = 150$, $R = 0.8$, coeff. $= 0.3$

Note: [a]The ratio $MaxIter_1/MaxIter_2 \approx 0.75$

Table II. Statistical results

	PSO	DE	Original PIO	ECPIO
Mean	15.42	28.99	7.32	*0.00*
Variance	59.05	16.36	33.44	*0.00*
Max	27.86	34.37	18.59	*0.00*
Min	5.97	19.53	1.17	*0.00*



Notes: (a) Base station with Septentrio receiver; (b) real signal acquisition with Stereo receiver

Figure 5. Base station measurement and real signal acquisition

Cartesian coordinates	Geodetic coordinates
BaseStation_X = 4,627,485.204 m	BaseStation_latitude = 43.56°
BaseStation_Y = 119,145.518 m	BaseStation_longitude = 1.47°
BaseStation_Z = 4,373,396.721 m	BaseStation_height = 209.647 m

Table III. Base station coordinates

Methods	ECPIOCD	CD
P_l	*0.90*	0.75
MBE(m)	*11,863.53*	16,441.50
MPE(m)	*1,135.65*	2,266.66
MCPh	*9*	7.40
ExT(s)	*5.78*	26.09
NPE	*180,100.00*	388,987.00

Table IV. Performance comparison between ECPIOCD and traditional CD

As can be seen from the results, both the MBE and the MPE values of ECPIOCD, which represent, respectively, the mean clock bias estimation error and the mean position estimation error, are smaller than those of traditional CD. This indicates that ECPIOCD has a relatively higher location precision than traditional CD. Moreover, in terms of P_l which indicates the stability and reliability of the algorithm utilized, ECPIOCD possesses a better performance. This implies that ECPIOCD is more likely to locate the receiver in weak signal environments than traditional CD. Such remark is supported by the results on MCPh which gives the number of correctly estimated code phases in 10. Besides, the mean number of points evaluated during the search of the receiver's correct location and clock bias is reduced to 180,100.00 which is less than half of that needed by traditional CD, and the execution time of ECPIOCD is divided by five compared to that of traditional CD. These prove that the proposed scheme has considerably accelerated CD algorithm.

In order to confirm the performance of ECPIO in the proposed scheme, acquisition simulations utilizing the proposed scheme with PSO, DE, PIO and ECPIO also first conducted, and the results are shown in Table V. With the same criteria, it can be found from the results that although PIO is quicker, it is still the ECPIO that performs the best, in terms of both precision and reliability.

Experiment with signals of 32-40 dB. As the proposed scheme with ECPIO turns out to possess the best performance on acquiring signal of 35 dB, further investigation on its acquisition performance for signals of different C/N_0 ratios is desired. Thus, experiments on simulated signals whose C/N_0 ratios are 32, 33, 34, 35, 36, 38 and 40 dB are conducted, with the power of noise fixed. In addition to the performance evaluation criteria above, the total error (TotE) is added. Statistical results are shown in Table VI, with the best marked in italic.

As can be seen from the results, for signals with different C/N_0, the proposed scheme generally outperforms the traditional CD, in terms of both precision indicated by MBE and MPE, stability or reliability measured by P_l and MCPh and execution time.

In fact, these improvements can be predicted directly from the design of the proposed scheme. In traditional CD, the search of the user's position is a grid-based search. This search mechanism's performance is lower compared to that of the proposed one.

First, in grid-based search, the search precision depends on the precision of the grid. However, the higher the grid precision is, the more points needs to be evaluated, and thus the higher the computational burden is. Therefore, the multi-resolution methods are proposed. In these methods, the search is conducted in several iterations, relocating the search center and reduce the search boundaries after each iteration. Nevertheless, as stated in section 3.2, there are lots of second highest peaks in the search domain. If after the first iteration, the highest peak (the true peak) is not included in the reduced

Table V. Performance comparison of different optimization methods

Methods	PSO	DE	PIO	ECPIO
P_l	0.05	0.1	0.25	*0.90*
MBE(m)	46,532.41	43,575.28	69,360.57	*11,863.53*
MPE(m)	6,704.35	7,893.44	8,069.54	*1,135.65*
MCPh	0.80	1.40	2.20	*9*
ExT(s)	6.84	9.58	*2.42*	5.78
NPE	180,100.00	180,100.00	*71,394.00*	180,100.00

C/N_0	Criteria	ECPIOCD	CD	C/N_0	Criteria	ECPIOCD	CD
32 dB	P_l	*0.40*	0.00	36 dB	P_l	*1.00*	0.90
	MBE	*55,647.54*	68,908.00		MBE	*11.19*	1,762.50
	MPE	*4,491.22*	7,827.73		MPE	*11.41*	295.39
	TotE	*55,828.48*	69,351.18		TotE	*15.98*	1,787.08
	MCPh	*3.75*	0.00		MCPh	*10.00*	8.90
	ExT	*5.79*	26.11		ExT	*5.97*	26.05
	NPE	*180,100.00*	388,987.00		NPE	*1,80,100.00*	388,987.00
33 dB	P_l	*0.40*	0.25	38 dB	P_l	*1.00*	*1.00*
	MBE	*44,469.36*	65,414.00		MBE	16.76	*15.00*
	MPE	*4,008.79*	5,946.36		MPE	*6.03*	34.53
	TotE	*44,649.69*	65,683.72		TotE	*17.81*	37.65
	MCPh	*4.20*	2.45		MCPh	*10.00*	*10.00*
	ExT	*5.79*	25.56		ExT	*6.03*	26.81
	NPE	*180,100.00*	388,987.00		NPE	*180,100.00*	388,987.00
34 dB	P_l	*0.65*	0.55	40 dB	P_l	*1.00*	*1.00*
	MBE	*21,995.20*	28,360.00		MBE	17.57	*10.50*
	MPE	*2,650.36*	2,891.65		MPE	*8.23*	32.11
	TotE	*22,154.31*	28,507.04		TotE	*19.40*	33.79
	MCPh	*6.55*	5.15		MCPh	*10.00*	*10.00*
	ExT	*5.88*	25.85		ExT	*5.88*	26.93
	NPE	*180,100.00*	388,987.00		NPE	*180,100.00*	388,987.00
35 dB	P_l	*0.90*	0.75				
	MBE	*11,863.53*	16,441.50				
	MPE	*1,135.65*	2,266.66				
	TotE	*11,917.76*	16,597.01				
	MCPh	*9.00*	7.40				
	ExT	*5.78*	26.09				
	NPE	*180,100.00*	388,987.00				

Table VI. Performance comparison with signals of different C/N_0

search domain, then the search will never get the correct position of the receiver. On the contrary, by the proposed approach, the search is conducted on a bounded set of real numbers. The highest peak is always included in the search domain. Therefore, the problem of grid-based search does not exist. With a high-performance algorithm, the user can be better located. This is the reason to the better direct location probability and the better location precision compared to the traditional CD.

Second, for grid-based search, the computation time depends highly on the number of dimensions, while for the proposed approach, the number of points evaluated is controlled by the number of individuals and that of iterations. For example, if n values are considered in each dimension, and there are m dimensions, then the total number of points is n^m by grid-based search, whereas by the proposed approach, it is at most $N_c(MaxIter_1 + MaxIter_2 + 1)$, independent of the number of dimensions. Therefore, if the search on Doppler frequency is also conducted (i.e. the carrier is not eliminated), the number of points evaluated for traditional CD will be n^{m+1}, while for the proposed approach, there will be only a slight increase. With fewer points evaluated, a shorter execution time is an inevitable outcome, which is also confirmed by the result.

6.3 Real signal experiments

With the same configurations as above, experiments based on real signals are also conducted. The acquisition environment is an indoor near window scenario which is a

rather hash environment for GNSS signal acquisition. The GNSS signals are received by the "Stereo" receiver, as is shown in Figure 4, which is at the same location with the BS in our case i.e. the real relative position of the receiver is (0,0,0) corresponding to (ΔN, ΔE, ΔD). For the relative clock bias (Δb), the receiver and the BS are considered to be synchronized. Under this assumption, the true value of Δb is supposed to be 0.

Different from simulated signal acquisition, in the real signal acquisition, the Doppler frequency shift must be taken into consideration. Therefore, in order to adapt the proposed algorithm into the real GPS signal acquisition, the Doppler frequency shift is considered as follows. For each satellite, another loop of frequency search is added (for both traditional CD and the proposed approach). The search range (*MedFreq* −10 kHz, *MedFreq*+10 kHz) is searched with a certain step (grid-search), where *MedFreq* denotes the intermediate frequency. The signal generated with each frequency shift is correlated with the input signal, and that give the highest peak is preserved. The results are shown in Table VII. As can be seen from the results, in a hash environment, the direct positioning accuracy of the proposed method and that of the traditional CD are of the same order of magnitude except the error in the east direction. However, the execution time spent by the proposed approach is much shorter than that spent by the traditional CD, especially from the point of view of the number of points evaluated.

Though the proposed approach is much more efficient and the traditional CD is a bit more accurate, the errors of both approaches are too large, especially that of the clock bias. This is partly caused by the hypothesis of synchronization between the BS and the "STEREO" receiver. They may be asynchronous in terms of clock bias. To make it clear, more research needs to be conducted with the synchronized receivers. Another reason is the hypothesis in the problem formulation part, in which we have eliminated the process of detection decision based on the detection probability. Therefore, more work needs to be conducted on the improvement of detection decision-making process which will further enhance the performance of ECPIOCD.

Besides, for the proposed approach, the performance of the application on the real GNSS signals can still be improved. The addition of the frequency loop is not the only choice, but a feasible proposal. Instead of adding a frequency loop, an additional dimension can be added, which only changes the reformulated optimization problem into a five-dimension optimization problem. Thus, the execution time will be further shortened and the accuracy may also be improved. However, to achieve this, a new question appears: can the Doppler frequency shift be calculated from the positions and velocities of the receiver and the satellites ? If it can be calculated in this way, then with the proposed idea, the performance on both the direct position estimation and the execution time will be considerably improved. This will be our next step work.

Table VII. Performance comparison between ECPIOCD and traditional CD for real signal acquisition

Methods	ECPIOCD	CD
BiasError	86,402.49	81,480.00
EastError	*844.84*	6,860.00
NorthError	3,919.03	*−3,540.00*
PosError	*4,009.06*	7,719.53
Execution time	*24.65*	98.03
Number of points	*180,100.00*	388,987.00

7. Conclusion and future work

In this work, a new CD scheme based on ECPIO is proposed to address the heavy computational burden of CD. Instead of grid-search methods, an improved optimization method is integrated into the CD scheme.

Experiments with simulated signals are conducted on both the proposed scheme and the traditional one. As the simulation results suggest, the proposed scheme generally outperforms the traditional in terms of both efficiency and accuracy. The execution time, in particular, is divided at least by 4. As for experiments with real signals, with the same accuracy (in terms of order of magnitude), the proposed scheme is much more efficient than the traditional one.

Our future work will mainly focus on two points:

(1) Improvement of detection decision-making process in order to further enhance the proposed approach.

(2) Implementation and improvement of the proposed scheme based on real signals. This work can still be separated into two parts:

- application of the proposed algorithm with synchronized receivers; and
- calculation of Doppler frequency shift from the positions and velocities of the receiver and the satellites.

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