An improved CS-LS hybrid algorithm on microseismic source location

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ABSTRACT
This paper presents a hybrid global optimization algorithm for the localization of microseismic events, which is composed of the Least-Squares (LS) algorithm and the Cuckoo search (CS) algorithm. It significantly reduces the demand for the accuracy of the inversion velocity model. The positioning process is presented as follows: firstly, construct an objective function by utilizing time difference information of P-wave; then, find the final optimal value through iterations by embedding this objective function as the fitness function to the hybrid algorithm. Through simulation experiments, the hybrid algorithm can acquire more accurate locations and a faster convergence speed than the LS algorithm.

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1. Introduction
The microseismic (MS) source location has been a hot research field for more than a hundred years (Batchelor et al., 1983). It plays a significant role in earthquake prediction, engineering earthquakes, earth structure research, and crustal stress analysis (Anikiev et al., 2014). The rapid determination of the seismic location provides very critical information for earthquake assessment and emergency rescue. Moreover, accurately determining the localization helps to identify seismogenic faults, studying the process of earthquake incubation and triggering (Maxwell et al., 2010). As a result, it is of great significance to determine the MS source. The technology is not only appraising the fracture but also saving resources (Grigoli et al., 2016). In consideration of the low permeability of these reservoirs (Han et al., 2020), improving the positioning accuracy has become one of the most urgent technology in oil exploitation. Only by improving the positioning accuracy can we promote the flow and acquisition of oil and gas reservoirs and finally achieve the purpose of increasing production (Fukui et al., 2017).

The accurate determination of artificial MS location has become the most considerable link in the subsequent analysis of fracturing effects. However, along with the increasing difficulty of drilling and mining, the location technology still faces immense challenges in addition to complex mining conditions (Witten & Shragge, 2017). For example, early location methods have required a high inversion velocity model and a high signal-to-noise ratio (SNR) (Duncan Peter & Eisner, 2010), which yield large location errors in practical applications. Besides, as for the MS location problem, most of them adopt a single algorithm in general. In particular, there are several negative aspects for using a single algorithm in MS location, such as the dependency on the velocity model/initial value, the trap into local optimum (Yaghini et al., 2013). Hence, on one hand, it is desirable to reduce the requirements of the velocity model and SNR; on the other hand, it is urgent to overcome the limitation of the single algorithm trapping into the secondary peak of value. This is the first motivation of our paper.

Thanks to the rapid development of computer technology, more and more optimization algorithms of swarm intelligence have been used to solve complex optimization problems. Compared with the traditional optimization algorithms, the intelligence optimization algorithm takes no account of any gradient information of the objective function, and it is easy to program on the computer (H. Dong et al., 2011). The Cuckoo search algorithm (CS), a new heuristic algorithm, has been proposed for various improved versions. Walton has developed a modified Cuckoo search strategy with a gradient-free method, which gets closer to the minimum as the number of objective function evaluations increases (Walton et al., 2011). Shehab has proposed tournament selection to replace the random selection in the standard CS algorithm, which efficiently avoids premature convergence (Shehab...
et al., 2017). Valian has replaced the fixed value Pa with a variable value in the CS algorithm, which enhances the accuracy and convergence rate of the CS algorithm (Valian et al., 2013).

The least-square algorithm (LS) is one of the traditional optimization algorithms. It uses a regression model to minimize the sum of residual squares of all observed values, and the ultimate goal is to obtain the extreme point of the square loss function. Lauria has proposed an improved least-square algorithm, which uses the expression of Cauchy principal value integral to decrease the computational burden and ensure high performance (Lauria & Pisani, 2014). Ismailova has proposed a modified least-square algorithm for the source location (Ismailova and Lu, 2015), where a weighted sum of squared terms is adopted to approach the global solution in order to get a high accuracy location. This paper aims to establish a uniform work to combine the CS algorithm with the LS scheme to solve the MS location problem. This desirable novel scheme is expected to take fully utilize the two existing algorithms.

In this article, we have investigated the MS location problems by a novel hybrid algorithm. The simulation result shows that the Cuckoo Least-squares hybrid (CS-LS) algorithm has better results than the LS algorithm. What’s more, the CS-LS algorithm is capable of locating a precise solution with a faster convergence rate and stable searchability. The main contributions are highlighted as follows:

1. The CS algorithm is improved to obtain an optimal value. More specifically, discovery probability, $P_a$, is set as an adaptive value, which can achieve the dynamic balance between global search and local search.
2. The initial value of the LS algorithm is set as the optimal value from the CS algorithm. Then, the LS algorithm continuously iterates until the residuals are minimized, which avoids the adverse impact on the algorithm performance due to the improper initial value.
3. A new hybrid algorithm is proposed with rapid convergence and stable performance, which has better performance than that of the Cuckoo search (CS) algorithm or the Least-squares (LS) algorithm.

This paper is outlined as follows. Section 2 introduces the microseismic source location model briefly. Section 3 presents the CS-LS algorithm. In Section 4, a number of simulation experiments are carried out to test the performance of the proposed algorithm. We end this paper with some conclusions in Section 5.

2. Microseismic source location model

2.1. The principle of microseismic location

Because the P-wave is easy to identify in practical engineering, the P-wave time difference of arrival has been picked through the geophones in many ground monitoring methods for locating MS events (Drew et al., 2005). In the classical approaches, the P-wave arrival times have been recorded at several geophones (Grechka et al., 2015). Then, the location model has been established based on the delayed difference of P-wave reaching different geophones by solving the source location (Li et al., 2013).

Suppose the geophone coordinates are $u(x_i, y_i, z_i)$, where $i = 0, 1, \ldots, m$. Moreover, $i = 0$ is set as the sensor standard criterion, and $0(x, y, z)$ is set as the source coordinates. It is assumed that the rock layers between the source and the geophone are the same. In general, the equivalent velocity of the P-wave propagating in the medium is $5.7 \text{m/ms}$ (where m refers to metre, ms denotes millisecond). The difference in the distance measured between any geophone $i$ and the source 0 is expressed as:

$$d_i = v \cdot (t_i - t_0) = \sqrt{(x - x_i)^2 + (y - y_i)^2 + (z - z_i)^2}$$

(1)

where $v$ represents the propagation velocity of the P-wave, $t_i$ represents the first arrival time received by the geophone, and $t_0$ represents the shock time of the seismic source. For the same simulated seismic source, the travel time fitting error of geophones $i$ and $j$ is $\Delta_{ij}$. The specific formula is given as follows:

$$\Delta_{ij} = d_i - d_j = v \cdot (t_i - t_0) - v \cdot (t_j - t_0).$$

(2)

It can be derived from formulas (1) and (2) that

$$d_i^2 = (\Delta_{ii} + d_j)^2 = (x_i^2 + y_i^2 + z_i^2) + (x_j^2 + y_j^2 + z_j^2) - 2(x_i x_j + y_i y_j + z_i z_j).$$

(3)

It can be derived from formula (3) that

$$d_i^2 - d_j^2 = (x_i^2 + y_i^2 + z_i^2) - (x_j^2 + y_j^2 + z_j^2) - 2(x_i - x_j)x - 2(y_i - y_j)y - 2(z_i - z_j)z.$$

(4)

Letting $j = i - 1$, it follows from the above equality that

$$2(x_i - x_{i-1})x + 2(y_i - y_{i-1})y + 2(z_i - z_{i-1})z - 2v^2 (t_i - t_{i-1})t_0$$

$$= x_i^2 - x_{i-1}^2 + y_i^2 - y_{i-1}^2 + z_i^2 - z_{i-1}^2 - v^2(t_i^2 - t_{i-1}^2)$$

$$i = 1, 2, \ldots, m).$$

(5)

For convenience, denoting the unknown information of the seismic source as $X_4 = [x, y, z, t_0]^T$, equation (5) are
represented by the following matrix equation

\[ A_{m \times 4}X_4 = B_m \]  

where

\[ A_{m \times 4} = \begin{bmatrix}
2(x_1 - x_0) & 2(y_1 - y_0) \\
\vdots & \vdots \\
2(x_m - x_{m-1}) & 2(y_m - y_{m-1}) \\
2(z_1 - z_0) & -2v^2(t_1 - t_0) \\
\vdots & \vdots \\
2(z_m - z_{m-1}) & -2v^2(t_m - t_{m-1}) 
\end{bmatrix} \]

\[ B_m = \begin{bmatrix}
x_1^2 - x_0^2 + y_1^2 - y_0^2 + z_1^2 \\
\ddots \\
x_m^2 - x_{m-1}^2 + y_m^2 - y_{m-1}^2 + z_m^2 \\
-2v^2(t_1 - t_0) \\
\cdots \\
-2v^2(t_m - t_{m-1})
\end{bmatrix} \]

In light of the number of the unknown variables, (6) has solutions if and only if \( m \geq 4 \). If \( m = 4 \), (6) has a unique solution; if \( m > n = 4 \), then (6) has no exact solution since it is overdetermined. Therefore, in three-dimensional (3-D) space, at least four geophones are required to determine the 3-D coordinates of the seismic source.

2.2. Microseismic objective function construction

From formula (3), \( \Delta_{ij} = 0 \) implies that the source location error is the smallest. As a result, according to formula (2), the source location formula can be transformed into the following optimization problem:

\[
\text{fitness} = \min \sum_{i,j=0,i \neq j}^m |\Delta_{ij}|
\]

s.t. \( x, y, z, t_0 \in \mathbb{R}; \quad i, j = 0, 1, \ldots, m \) (7)

Accordingly, the locations of the unknown seismic source can be obtained by solving the formula (7).

In this paper, the objective function is the key to the success of the experiment. In the process of the iteration, the value of the objective function is 0 or close to 0, and therefore the source coordinates obtained are more accurate.

3. The CS-LS algorithm

3.1. The cuckoo search algorithm

Cuckoos, a kind of birds with a unique reproductive function, are so aggressive who lay eggs without build nests and foster eggs in a communal nest (Mareli & Twala, 2018). They also remove other eggs to increase the probability of hatching their own eggs (Ouaarab et al., 2014). The host bird helps to hatch the baby cuckoos in their nest, and the baby cuckoos have similar features to the host birds, like egg size, colour, hatching period, brooding period, and chick feeding habits (Goyal & Patt Henrik, 2014). The purpose of their behaviours is to increase the probability of legitimate eggs from hatching and gain access to more food. In light of the breeding strategy of cuckoo parasitic brooding, the CS algorithm has been proposed as a new kind of heuristic algorithms [21]. More specifically, it was raised by Yang, a scholar at the University of Cambridge, in 2009 (Yang & Deb, 2009). In what follows, there are three ideal rules based on the CS algorithm:

1. Each cuckoo lays only one egg at a time and selects the host bird nest randomly;
2. In a group of bird nests found by random selection, keep the best bird’s nest (solution) for the next generation;
3. The number of host bird’s nests is sure, and the probability of the host finding foreign eggs is \( p_o \in (0, 1) \), which is the probability of the host bird creating a new bird’s nest. Meanwhile, the host bird can discard or throw the alien egg away from its own nest directly. Also, it can build a fire-new bird’s nest elsewhere (Gandomi et al., 2013).

The core of the cuckoo search algorithm is two-position update formulas, i.e. local search and global search.

The search path of the \( (t + 1) \) generation cuckoo and the update formula of the bird’s nest position are given as follows:

\[ x_i^{t+1} = x_i^t + \alpha \oplus L(\lambda) \] (8)

where \( x_i^{t+1} \) represents the location of the new generation of birds nest, \( x_i^t \) represents the location of the \( i \)th bird’s nest in the \( t \) generation, \( \oplus \) is the dot multiplication, and \( \alpha \) is the step length factor, which is employed to control the random search range.

In this paper, set \( \alpha = 0.01 \), which is verified by experiment. \( L(\lambda) \) is also denoted as Levy(\( \lambda \)), which represents a casual search path, which obeys the Levy distribution with the parameter \( \lambda \). Equation (8) is essentially a random walking equation. Generally, a random walk is a Markov chain, and its future localization depends on the current location (the first term of (8)) and the transition probability (the second term of (8)).

Levy flight is a random walk in which the probability distribution of step size is heavy tail distribution, and the
direction of each step is virtually random and isotropic. That is to say, the process of random walking has a relatively high probability of large stride (Senthilnath et al., 2013). What’s more, the variance of Levy flight is exponential with time. Compared to normal random walking, it can reduce the iterations of the CS algorithm on a large scale.

Levy(λ) obeys the Levy distribution, as shown below:

$$\text{Levy}(\lambda) = t^{-\lambda}$$  \hspace{1cm} (9)

where $1 < \lambda \leq 3$.

The Levy distribution is generated by:

$$\text{Levy}(\beta) = \frac{\mu}{|\nu|^\beta}$$  \hspace{1cm} (10)

where $\lambda = 1 + \beta$, $\beta \in (0, 2]$, and $\beta = 1.5$. Moreover, the parameters $\mu$ and $\nu$ obey the normal distributions, i.e. $\mu \sim N(0, \sigma_\mu^2)$ and $\nu \sim N(0, \sigma_\nu^2)$, where $\sigma_\mu = \frac{\Gamma(1+\beta) \sin(\pi \beta)}{\Gamma(\frac{1+\beta}{2}) \beta^{\frac{\beta}{2}}}$ and $\sigma_\nu = 1$.

By resorting to (10), the updating formula of the bird’s nest position (8) is rewritten as

$$x_{i+1}^t = x_i^t + \alpha \frac{\phi \mu}{|\nu|^\beta} (x_i^t - x_{\text{best}}^t).$$  \hspace{1cm} (11)

When the location is updated, compare the random number $r \in [0, 1]$ with the discovery probability $p_a \in [0, 1]$. If $r < p_a$, randomly change the location $x_{i+1}$ and discard a small part of the defective birds’ nest. According to the random walk, the same number of bird nests is generated as abandoned bird nests. Then, a group of new bird nests is produced by adding them with the un-abandoned bird nests after that. The purpose of such a procedure is to avoid the location falling into the local optimum. If $r \geq p_a$, then the location is fixed. Finally, the better position of bird’s nests in a group is reserved, which is represented as $x_{i+1}$. That is,

$$x_{i+1}^t = x_i^t + r(x_i^t - x_a^t)$$  \hspace{1cm} (12)

where $x_i^t$ and $x_a^t$ are two random solutions.

### 3.2. An improved cuckoo search algorithm

In the standard CS algorithm, although the length of the search step can change randomly, it causes slow convergence speed in the later stage when searching local optimal solutions (Cui et al., 2017). To accelerate the convergence speed and avoid falling into the local optimum, the improved parameters $p_a$, an adaptive value, helps to achieve the dynamic balance of global search and local search (Valian et al., 2013). It can also adjust the convergence rate of the algorithm (Abdel-Baset et al., 2018). As a result, this improvement has several advantages, such as enhancing the algorithms’ convergence rate, exploring the search space better, and finding the region of the global minimum (Yildiz, 2013).

The adaptive strategy proposed in this paper for the parameter $p_a$ is:

$$p_a^t = p_{\text{max}} - (p_{\text{max}} - p_{\text{min}}) e^{-\frac{t}{T}}.$$  \hspace{1cm} (13)

where $t$ is the current iteration number and $T$ is the total iteration number. According to the empirical value, choose $p_{\text{min}} = 0.1$, $p_{\text{max}} = 0.75$. The use of a non-linear incremental dynamic adjustment mechanism for the $p_a$ can make the algorithm have a relatively small $p_a$ value at the beginning of the iteration. At this time, there are more renewed bird nests, so that the algorithm has strong global searching ability. When entering the later iteration, the value of $p_a$ is relatively large, which updates the number of bird nests slowly. Moreover, owing to its strong local searching ability, the convergence of the algorithm is improved, which helps the particles to jump out of the local optimum solution.

### 3.3. The least-squares algorithm

The least-square algorithm (LS) is a mathematical optimization algorithm (Caponnetto & De Vito, 2007), also known as the least square method. The best matching result of the data is found by minimizing the error square (Dennis et al., 1981).

From formula (3), one acquires the following formula:

$$r_{i,0} \triangleq d_i - d_0 = \sqrt{(x-x_i)^2 + (y-y_i)^2 + (z-z_i)^2} - \sqrt{(x-x_0)^2 + (y-y_0)^2 + (z-z_0)^2}.$$  \hspace{1cm} (14)

Denoting

$$d_i \triangleq \sqrt{(x-x_i)^2 + (y-y_i)^2 + (z-z_i)^2},$$  \hspace{1cm} (15)

one then has

$$d_i^2 = (x^2 + y^2 + z^2) + (x_i^2 + y_i^2 + z_i^2) - 2(x x_i + y y_i + z z_i).$$  \hspace{1cm} (16)

On the other hand, it can be obtained that:

$$d_i^2 = (r_{i,0} + d_0)^2,$$  \hspace{1cm} (17)

and we then have:

$$d_i^2 = r_{i,0}^2 + 2r_{i,0}d_0 + d_0^2 = (x^2 + y^2 + z^2) + (x_i^2 + y_i^2 + z_i^2) - 2(x x_i + y y_i + z z_i).$$  \hspace{1cm} (18)
According to formula (14), one has
\[
d_2^2 - d_0^2 = (x^2 + y^2 + z^2) + (x_i^2 + y_i^2 + z_i^2)
\]
\[
- 2(xx_i + yy_i + zz_i) + 2(xx_0 + yy_0 + zz_0).
\]
\[
(19)
\]
For convenience, define the following notations:
\[
k_i \equiv x_i^2 + y_i^2 + z_i^2, \quad k_0 \equiv x_0^2 + y_0^2 + z_0^2, \quad x_i,0 \equiv x_i - x_0,
\]
\[
y_i,0 \equiv y_i - y_0, \quad z_i,0 \equiv z_i - z_0.
\]
\[
(20)
\]
It follows from (19) that:
\[
d_2^2 - d_0^2 = (k_i - k_0) - 2(xx_i,0 + yy_i,0 + zz_i,0).
\]
\[
(21)
\]
Combining (17) with (20), we obtain the following formula:
\[
-2(xx_i,0 + yy_i,0 + zz_i,0) = r_{2i,0}^2 + 2r_{1i,0}d_0 - k_i + k_0.
\]
\[
(22)
\]
Denoting \(X_3 = [x \ y \ z]^T\), (22) is rewritten as the following matrix form:
\[
A_{m \times 3}X_3 = B_m
\]
where
\[
A_{m \times 3} = \begin{bmatrix}
x_{1,0} & y_{1,0} & z_{1,0} \\
\vdots & \vdots & \vdots \\
x_{m,0} & y_{m,0} & z_{m,0}
\end{bmatrix},
\]
\[
B_m = -\frac{1}{2} \begin{bmatrix}
r_{1,0}^2 + 2r_{1,0}d_0 - k_i + k_0 \\
\vdots \\
r_{m,0}^2 + 2r_{m,0}d_0 - k_m + k_0
\end{bmatrix}.
\]
Finally, the source position can be obtained by the pseudo-inverse method, i.e. \(X_3 = (A_{m \times 3}^T A_{m \times 3})^{-1} A_{m \times 3}^T B_m\).

### 3.4. The improved cuckoo least-squares hybrid algorithm

The Levy flight of the CS algorithm has high random characteristics, which makes the search process jump from one area to another quickly. Thus, the CS algorithm has a strong global searching capability. Nevertheless, the high randomness of the flight leads to the aimless search process, and the convergence speed becomes very slow (Chi et al., 2019). When the search process comes to near the optimal solution, the search efficiency is very low. The LS algorithm is a relatively simple calculation, which runs fast and convenient without repeated iterative steps (Bouyer & Hatamlou, 2018). Simultaneously, the advantage of the LS algorithm is more convenient to deal with the positioning problem, which hugely reduces the calculation amount of objective function. The algorithm relies too much on the selection of the initial value. If the improper value is selected, the positioning error will be obvious.

Aiming at the strong points and drawbacks of the CS algorithm and the LS algorithm, we propose an improved Cuckoo Least-Squares hybrid location (CS-LS) algorithm by combining the strong points of these two algorithms. The CS-LS algorithm not only improves location accuracy but also achieves the effect of high precision. In a word, the hybrid algorithm has a short search time and high calculation efficiency (Ibrahim & Tawhid, 2019). The flow chart of the CS-LS algorithm is presented in Figure 1.

In the following, the main steps of the algorithm are listed as follows:

1. Initialize the parameters required in the CS algorithm, including population size \(N\), search space dimension \(D\), discovery probability \(p_d(p_{\text{amin}}, p_{\text{amax}})\) and the maximum number of iterations \(T\), etc;
2. Randomly generate \(n\) bird nest positions, calculate the corresponding fitness value of each bird nest position, and select the initial global optimal bird nest position;
3. Keep the best nest position of the previous generations, and then use the step-size updating formula of
the CS algorithm with the Levy flight mechanism to update the location to get the new nest position;

(4) Update the best historical position of the birds’ nest. Then compare it with the previous birds’ generation of nest position and fitness function;

(5) Compare the uniformly distributed random number \( r \in (0, 1) \) with the discovery probability \( p_a \), which is found by the nest owner, and keep the nest position with the lower \( p_a \). At the same time, perform the bird’s nest position with a higher discovery probability by random processing. Then obtain a new set of bird’s nest positions. Comparing this set of bird’s nest positions with nest position in step 4, then replace the poorer bird’s nest positions to obtain the contemporary global best bird’s nest location;

(6) The global optimal birds’ nest position, obtained in step 5, is regarded as the initial value in the LS algorithm. The purpose is to acquire an accurate target search;

(7) Once the termination condition is acquired, end the algorithm, and then output the final global optimal value. If not, return to step 3 to continue iterating until every requirement is satisfied.

According to the above steps, the pseudo-code is summarized as follows.

**Algorithm 1** The Improved Cuckoo Least-Squares Hybrid Algorithm

**Initialization:** \( N \leftarrow 25, D \leftarrow 3, p_{\text{amin}} \leftarrow 0.15, p_{\text{amax}} \leftarrow 0.55, T \leftarrow 150 \)

1. Set objective function \( f(x) = (x_1, \ldots, x_d)^T \)
2. Set an initial population of \( N \) host birds \( x_i \)
3. while \( t < (\text{MaxGeneration}) \) or (stop criterion) do
   4. Randomly select a cuckoo
   5. Search a new solution through Levy flight
   6. Evaluate the quality of the solution or the objective function value \( f_i \)
   7. Randomly select one nest from \( n \) nests (set to \( j \))
   8. if \( f_i < f_j \) then
      9. Replace the value of \( f_i \) with the value of \( f_j \)
   10. end if
   11. Abandon some nests with bad probability values \( (p_a) \)
   12. Generate the new nest value by Formula \( x_i^{t+1} = x_i^t + \alpha \odot L(\lambda) \)
   13. Save global optimal solution
   14. Regard the global optimal birds’ nest position as the initial value in the LS algorithm
   15. Acquire the final value
   16. \( t \leftarrow t + 1 \)
   17. end while

In a word, there are several advantages for the LS algorithm to carry out the experiments of MS location directly. The most convenient operation is that it can avoid derivation problems, which means there is no need to calculate the gradient of the objective function. In other words, the LS algorithm has very high requirements for the speed model. The CS algorithm is a random iterative optimization method, but also a non-derivative optimization algorithm. In the hybrid localization algorithm, the CS algorithm is to seek initial optimization firstly. When the CS algorithm is finished, the MS location has ranged to a certain extent. That means a rough location value is obtained. This value can better cover the possible MS locations of the optimal solution. Then the value is used as the initial value of the LS algorithm for accurate optimization. After the iteration of the LS algorithm, the optimal solution is judged by the expectation. If it meets the expectation, the optimization result is taken as the final output. Conversely, continue iterating until the requirements are satisfied.

### 4. Simulation experiment results and positioning performance analysis

In the location of the MS source, the effectiveness and accuracy of the hybrid CS-LS algorithm are verified through the following experiment. In this experiment, ten geophones are deployed in 3-D space, the onset time of microseismic is set as 0s, and three seismic sources are chosen in 3-D space, where the locations are set as \((20, 60, 35), (30, 90, 85)\) and \((70, 60, 40)\). Table 1 shows the location and first arrival time of each geophone.

| Geophone coordinates | Time of first arrival/ms |
|----------------------|-------------------------|
| Numbering | \( x/m \) | \( y/m \) | \( z/m \) | |
| 1 | 0 | 0 | 100 | 341.37 |
| 2 | 100 | 0 | 100 | 325.97 |
| 3 | 0 | 100 | 100 | 375.42 |
| 4 | 100 | 100 | 100 | 298.56 |
| 5 | 0 | 0 | 0 | 277.53 |
| 6 | 100 | 0 | 0 | 255.39 |
| 7 | 0 | 100 | 0 | 299.88 |
| 8 | 100 | 0 | 100 | 327.55 |
| 9 | 37 | 65 | 39 | 177.79 |
| 10 | 60 | 40 | 10 | 159.61 |

**4.1. Verification idea**

This experiment is based on the cube velocity model, using the time difference information to accomplish the MS location. Among them, the principal technology is to adopt the time difference of the P-wave to different geophones building equation set. Then, compare the location of the LS algorithm with that of the CS-LS hybrid.
Table 2. The performance comparisons between LS algorithm and CS-LS algorithm.

| Focal coordinates $M_1$ | Algorithm name | Performance metrics | X/m  | Y/m  | Z/m  | RMSE/m |
|-------------------------|----------------|---------------------|------|------|------|--------|
| LS algorithm            | Mean convergence value | 21.1940            | 59.5771 | 35.8549 | 5.7638 |
| True Value              | 20             | 60                 | 35   |      |      |
| Error                   | 1.1940         | 0.4229             | 0.8549 |      |      |
| CS-LS algorithm         | Mean Convergence Value | 20.0081            | 59.9997 | 35.0167 | 0.1123 |
| True Value              | 20             | 60                 | 35   |      |      |
| Error                   | 0.0081         | 0.0003             | 0.0167 |      |      |

| Focal coordinates $M_2$ | Algorithm name | Performance metrics | X/m  | Y/m  | Z/m  | RMSE/m |
|-------------------------|----------------|---------------------|------|------|------|--------|
| LS algorithm            | Mean convergence value | 24.0142            | 89.6862 | 84.8933 | 4.1435 |
| True Value              | 30             | 90                 | 85   |      |      |
| Error                   | 5.9858         | 0.3138             | 0.0106 |      |      |
| CS-LS algorithm         | Mean convergence value | 30.0031            | 90.0174 | 85.0198 | 0.0963 |
| True Value              | 30             | 90                 | 85   |      |      |
| Error                   | 0.0031         | 0.0017             | 0.0198 |      |      |

| Focal coordinates $M_3$ | Algorithm name | Performance metrics | X/m  | Y/m  | Z/m  | RMSE/m |
|-------------------------|----------------|---------------------|------|------|------|--------|
| LS algorithm            | Mean convergence value | 67.0298            | 58.5485 | 41.4029 | 6.8843 |
| True Value              | 70             | 60                 | 40   |      |      |
| Error                   | 2.9702         | 1.4515             | 1.4029 |      |      |
| CS-LS algorithm         | Mean convergence value | 70.0135            | 59.9718 | 40.0067 | 0.1093 |
| True Value              | 70             | 60                 | 40   |      |      |
| Error                   | 0.0135         | 0.0282             | 0.0067 |      |      |

algorithm in 3-D independently. After a comparative analysis of the location accuracy and convergence speed, we can obtain the pros and cons of the algorithms. Accordingly, to ensure the accuracy of the experimental results, 25 random experiments are conducted on the two algorithms in the same speed model (Zhebel & Eisner, 2015). The root mean square error (RMSE) and the error bar graph are employed to analyze the location error of the simulation results.

4.2. Experimental results and verification analysis

The LS algorithm and the improved CS-LS hybrid algorithm are utilized to analyze and calculate three verified optimums, which are $M_1(20, 60, 35)$, $M_2(30, 90, 85)$, and $M_3(70, 60, 40)$, respectively. Then, the location error and RMSE of the source coordinates are calculated successively, where the RMSE formula of the three-dimensional coordinates is given as:

$$\text{RMSE} = \sqrt{\frac{1}{n} \left[ (x - x_{id})^2 + (y - y_{id})^2 + (z - z_{id})^2 \right]}.$$  \hspace{1cm} (24)

where $n$ is the total number of random experiments, $(x, y, z)$ represents the coordinates of the microseismic location, which are the verified locations, and $(x_{id}, y_{id}, z_{id})$ expresses the source coordinates, which are acquired from the experiment. In this paper, set $n = 25$. Table 2 shows the convergence value, positioning error, and RMSE using the LS algorithm and the hybrid CS-LS algorithm, respectively.

Based on the above experimental analysis, there are 25 groups of random trials performed on each verification location to ensure the accuracy of the experimental results. The data of extreme maximum value and minimum value need to weed out. Then, the remaining 23 groups’ data are chosen to analyze the value of RMSE. It is observed from the simulation results that no matter which location point is verified, the source location obtained by the improved hybrid CS-LS algorithm is more precise than that of the LS algorithm. Simultaneously, the proposed algorithm has the smallest RMSE value in comparison with the LS algorithm. As a case in points, the result in focal coordinate $M_1(20, 60, 35)$, the CS-LS algorithm converges to the global optimum $(20.0081, 59.9997, 35.0167)$, the LS algorithm converges to $(21.1940, 59.5771, 35.8549)$, which verifies the advantages of the CS-LS algorithm in positioning accuracy once again. To sum it up, the solution quality of the improved hybrid CS-LS algorithm is better than that of the LS algorithm. Also, it has higher positioning accuracy, stable results, and higher search efficiency.

For each verified location point, this article tests 25 groups of random experiment data. To more intuitively reflect the location accuracy of the random experiment, the following scatter plots show the location values obtained by the two algorithms to visualize their distribution in the 3-D space with different colours. Based on the scatter plots of the improved CS-LS algorithm and the LS algorithm in Figures 2–4, it is clear that the proposed CS-LS algorithm, in the 3-D space, is denser and closer to
the locations than that of the LS algorithm. In contrast, the positioning scatters of the LS algorithm in 3-D space is more disperse, and the random error is relatively large.

Next, the error bar graph is applied to investigate the performance of the CS-LS algorithm. The magnitude of the location error of the seismic source location in three coordinate axis directions are plotted in Figures 5–7. Taking location point $M_1(20, 60, 35)$ as a representative, the LS algorithm and the improved CS-LS algorithm are employed respectively to analyze the positioning error from the three directions of the coordinate axis. The overall results in Figures 5–7 show that the hybrid CS-LS algorithm has tiny error fluctuations, which is nearly a straight line. The LS algorithm has a large floating on the error bar graph and two forms compared obviously, which further shows that the improved CS-LS algorithm has a higher positioning accuracy.

In the basic CS algorithm, Levy flight has relatively large blindness due to its randomness characteristics, which yields the slower convergence speed of the algorithm to the global optimal value in the subsequent iterations. In this paper, the discovery probability of the algorithm has adopted an adaptive adjustment mechanism to acquire positioning value firstly. Afterward, the obtained positioning value has been utilized as the initial value to iterate in the LS algorithm further. As a result, the accuracy of the microseismic location improved significantly. The following three-dimensional figure shows the verified positioning points with the location point of the improved CS-LS algorithm. It looks so intuitively
that whether the improved CS-LS algorithm reaches the
global optimal value more accurately. Among them,
Figure 8 describes the positioning map of the verifica-
tion positioning point $M_1$, and the convergence co-
ordinates are (19.9998, 59.9999, 35.0002). Figure 9 is the
positioning map of the verification positioning point $M_2$,
and the convergence coordinates are (30.0002, 89.9991,
84.9999). Figure 10 plots the positioning map of the posi-
tioning point $M_3$, where the convergence coordinates are
(69.9997, 60, 39.9999).

As we know, in the improved CS-LS algorithm, the fit-
ness function varies with the iterative process, which is
shown in Figure 11. The experimental result shows that
the improved CS-LS positioning algorithm can obtain a
high-precision global optimal value with a smaller num-
ber of iterations times.

Finally, two optimization algorithms are employed
to calculate the locate error. Through comparative
experiments in Figures 12–13, the improved hybrid CS-
LS algorithm has smaller positioning error fluctuations,
which implies that the deviation between the estimated
location and the actual verified location is tinier. It also
shows that the improved hybrid CS-LS algorithm is more
stable and can more effectively improve the positioning accuracy of the MS source.

5. Conclusion and outlook

The hybrid CS-LS algorithm has been proposed to achieve high precision for locating MS events using only the P-wave arrival times. The standard CS algorithm is easy enough to fall into the local optimum. The discovery probability has been improved in the CS algorithm, which has the advantages of a few setting parameters and fast convergence speed. This improved CS algorithm has been developed in this paper to find the optimal value firstly, which is regarded as the initial value of the LS algorithm. After solving twice, a highly accurate source location has been obtained with a high convergence rate. Meanwhile, the high accuracy requirements of initial value have been met for the LS algorithm, which also reflects the superiority of the hybrid algorithm.

In future, in the field of MS source location, the accuracy of the velocity model can also be in-depth explored when facing different oilfield environments with actual geological conditions. This is conducive to achieving high-efficiency and resource-saving MS positioning precisely.

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