Response to comments

Dear Editors and Reviewers,

On behalf of my co-authors, we thank you very much for giving us an opportunity to revise our manuscript, we appreciate editor and reviewers very much for their positive and constructive comments and suggestions on our manuscript.

We have studied comments carefully and have made correction which we hope meet with approval. Attached please find the revised version, which we would like to submit for your kind consideration.

We would like to express our great appreciation to you and reviewers for comments on our paper. Looking forward to hearing from you.

Thank you and best regards!

Yours sincerely,

Rui-Sheng Jia
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Q1: Page 1, Line 12: change into "discrepancies between differences of modeled arrival times and differences of measured arrival times". This correction was suggested also in the first revision, but it has been ignored by you.

R1: We are very sorry for our negligence of "differences of", and we have revised it. Refer to P1L10-11.

Q2: Page 2, Line 6: remove the word "time" in the sentence "Waldhauser and Ellsworth (2000) presented earthquake location algorithm based on a double time differences". The concept presented by Waldhauser and Ellsworth is "double difference" and not "double time differences". This correction was suggested also in the first revision, but it has been ignored by you.

R2: We have revised it. Refer to P2L4.

Q3: Page 2, line 30 – Page 3 line 4: Please, reformulate in that way: "Assign the microseismic source …, the coordinates of each geophone …., the time of P-wave arrival to i-th geophone …. and the origin time of the microseismic event as t0. Assuming that the rock layers between the microseismic sources and the geophone are uniform (i.e. uniform velocity model), the equivalent average propagation velocity of the P-wave in the medium is V.

R3: We have made correction according to the Reviewer's comments. Refer to P2L27-P3L1.

Q4: Page 3, line 19: In the revised version of the manuscript, you now refer to measured data or differences between measured data with the symbol ‘. Now, instead, you use the symbol ^, which was used in the first version of the manuscript .Please substitute with ‘ symbol, also in the following equations.

Page 4, line 2: substitute to with t0.

R4: We have made correction according to the Reviewer's comments. Refer to P3L16-17, L20.

Q5: Page 4, line 6: Insert a space between "solution" and "the"

R5: We have made correction according to the Reviewer's comments. Refer to P4L3.

Q6: Page 5, line 9: Please specify what each d-th component of the particles represent in this work. You can also

write it in the section 3.2, but in my opinion it is important to clearly define it, without leaving the reader autonomously understand it.
R6: We have made correction according to the Reviewer's comments. Refer to P5L11-12.

Q7: Page 6, line 5: Insert a space between "initialization" and "of".
R7: We have made correction according to the Reviewer's comments. Refer to P6L2.

Q8: Page 7, line 8: reformulate as follows: "optimization problems are divided into local and global problems. The former consists in looking for the minimum …, the latter …."
R8: We have made correction according to the Reviewer's comments. Refer to P6L21-23.

Q9: Page 7, line 25: I still do not understand what is the "initial value of evolutionary generations". Please, be clearer.
R9: We have made correction according to the Reviewer's comments. Refer to P7L7.

Q10: Page 9, line 7: I still do not understand the meaning of N.
R10: We have revised it and add a reference. Refer to P8L11-17.

Q11: Page 9, line 11: What are the coordinates of S? It is not represented in the plot.
R11: We have deleted it. Refer to P8L21.

Q12: Page 9, figure 2: As in the first revision, I suggest you again to work on the figure, by adding the dimensions of the cube and by putting a symbol (for example a triangle) where the receivers are located.
R12: We have revised it according to the Reviewer's comments. Refer to P9, Fig. 2.

Q13: Page 10, line 1 and following: No efforts have been done to improve the clarity of this paragraph. Some suggestions: First, the synthetic travel times have been computed. Then, the differences between the arrival times at all the pairs of stations have been retrieved according to equation (n) … and so on.
This paragraph is very important, and the greatest clarity as possible is requested.
R13: We have revised it according to the Reviewer's comments. Refer to P9L5-7.

Q14: Page 11: In the previous revision I asked you to specify how you chose the initial values. Furthermore, it was not clear to me why you mentioned different initial values if only a starting solution was provided in table 3. Neither answers nor modifications have been done concerning my comment. Please work on it.
R14: We have added an explanation for the initial value, Refer to P10L5-10.

Q15: Page 13: Please add a figure showing an example of real datum (seismogram).
R15: We have added a figure according to the reviewer's suggestion. Refer to P14, Fig. 6.

We tried our best to improve the manuscript and made some changes in the manuscript. These changes will not influence the content and framework of the paper. And here we did not list the changes but marked in red in revised paper. (2nd-Revised manuscript(Marked with red).pdf)

The adaptive particle swarm optimization technique for solving microseismic source location parameters

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Abstract. An intelligent method is presented for locating microseismic source based on particle swarm optimization (PSO) concept. It eliminates microseismic source locating errors caused by inaccurate velocity model of the earth medium. The method uses as the target of PSO a global minimum of the sum of squared discrepancies between differences of modeled arrival times and differences of measured arrival times. The discrepancies are calculated for all pairs of detectors of a seismic monitoring system, Then, the adaptive PSO algorithm is applied to locate the microseismic source and obtain optimal value of the P-wave velocity. The PSO algorithm adjusts inertia weight, accelerating constants, the maximum flight velocity of particles, and other parameters to avoid the PSO algorithm trapping by local optima during the solution process. The origin time of the microseismic event is estimated by minimizing the sum of squared discrepancies between the modeled arrival times and the measured arrival times. This sum is calculated using the obtained estimates of the microseismic source coordinates and P-wave velocity. The effectiveness of the PSO algorithm was verified through inversion of a theoretical model and two analyses of actual data from mine blasts in different locations. Compared with the classic least squares method, the PSO algorithm displays faster convergence and higher accuracy of microseismic source locating. Moreover, there is no need to measure the microseismic wave velocityin advance: the PSO algorithm eliminates the adverse effects caused by error in the P-wave velocity when locating a microseismic source using traditional methods.

1. Introduction

Microseismic monitoring technology can be used for effective locating rockruptures caused by rock burst, coal and gas outburst, water inrush, and other coalmine disasters. In recent years it was also used in early warning systems (Li et al.,2016; Pastén et al., 2015; Jia et al., 2015). The spatial coordinates of monitoring stations and the arrival times of the first seismic wave are used to determine the coordinates of the microseismic source, origin time, and other attributes. The accuracy of microseismic source location has been an important research topic in microseismic monitoring technology for a long time.

Current microseismic source location methods mostly come from seismology. Now they are widely used in microseismic monitoring (Sun et al., 2016; Xue et al., 2015; Anikiev et al., 2014; Dong and Li, 2013). The earthquake source location method, based on time-difference principles was proposed (Geiger,1912). Based on this work, Lienert et al. (1986)

developed an improved algorithm called HYPOCENTER. Since then, Nelson and Vidale (1990) presented the QUAKE3D method for 3-D velocity modeling. Lomax et al. (2000; 2001) worked out a nonlinear mode for locating global earthquakes in 3-D media and developed NonLinLoc software. Waldhauser and Ellsworth (2000) presented earthquake location algorithm based on a double time differences and developed HypoDD software. After occurrence of characteristics of the coal mine overburden layers andabscission zones, Gong et al. (2012) proposed a microseismic detecting algorithm for isotropic velocity model along mine length; the algorithm decreases source location errors. Dong et al. (2017) proposed mathematical algorithms of microseismic source location where there is no need to predict velocity inadvance. The algorithms overcome location errors caused by errors of velocity measurement inherent in traditional location methods. Lin et al. (2010) analyzed the characteristics of linear location method and Geiger method and proposed a joint method to address the problem of low precision in estimation of source coordinates inherent in linear location method. Feng et al. (2015) proposed stratified methods for microseismic source location based on particle swarm optimization to obtain correlations among the source position, origin time, and microseismic propagation speed for a non-unique solution.

In conclusion we note that the microseismic source location accuracy is influencedby many factors such as the location method, the layout of the microseismic network, the velocity model, and the accuracy of the arrival time measurement (Dong and Li, 2013). Among these, the key factor influencing the stability of the location algorithm and the location accuracy is precision of the velocity model (Prange et al., 2015; Li et al., 2014; Usher et al., 2013). In this paper, an adaptive particle swarm optimization algorithm is proposed for microseismic source location which is based on average flying velocity of the particles. It uses as the PSO target function the "least square sum" of measured arrival time differences for all pairs of seismic sensors and uses the PSO algorithm to identify the source coordinates and microseismic wave velocity. Then, the origin time of the microseismic event is calculated according to the just determined source location and the wave velocity. Parameters of the PSO algorithm such as the inertia weight, the acceleration constants and the flight velocities of particles are adaptively adjusted to avoid the algorithm failure caused by the improper selection of these parameters. Careful dynamic adjusting PSO parameters improves the robustness of the PSO algorithm, reduces number of iteration and improves estimation of the microseismic source coordinates and the seismic wave velocity.

2. Microseismic source location principle

Suppose, that there are *n* geophones in the microseismic monitoring system. Assign the microseismic source location point as $r_0=\left(x_0,y_0,z_0\right)$, the coordinates of each geophone as $r_i=\left(x_i,y_i,z_i\right),\left(i=1,\ldots,n\right)$. the time of P-wave arrival to *i-th* geophone of the microseismic monitoring system as t_i, and the origin time of the microseismic event as t_0. Assuming that the rock layers between the microseismic sources and the geophone are uniform (i.e. uniform velocity model), the equivalent average propagation velocity of the P-wave in the medium ias *V*, the time of the source P-wave arrivalto *i-th* geophone of the

~~microseismic monitoring system as t_i, and the origin time of the microseismic event as t_0.~~ Then, the theoretical (regression) arrival time differences for i and j geophones are

$$\Delta t_{i,j} = t_i - t_j = \frac{l_i - l_j}{V}, i, j = (1, \ldots, n), \tag{1}$$

where

$$\begin{cases} l_i = \sqrt{(x_i - x_0)^2 + (y_i - y_0)^2 + (z_i - z_0)^2} \\ l_j = \sqrt{(x_j - x_0)^2 + (y_j - y_0)^2 + (z_j - z_0)^2} \end{cases}.$$

The differences between the difference of regression arrival times $\Delta t_{i,j}(r_0)$ and the difference of the measuredarrival times $\Delta t'_{i,j}$ is analogous to double-difference concept introduced by Waldhauser and Ellsworth (2000).The sum of their squares reflect the degree of discrepancies between regression and observed arrival times. The equation for estimation of the microseismic source position has the form:

$$Q(r_0, V) = \sum_{i,j=1}^{n} \left(\Delta t'_{i,j} - \frac{l_i(r_0) - l_j(r_0)}{V} \right)^2 = \min_{r_0, V}. \tag{2}$$

The estimates of microseismic source coordinates $\hat{r}_0 = (\hat{x}_0, \hat{y}_0, \hat{z}_0)$ and equivalent P-wave velocity in the medium $\hat{V}$ correspond to those values of $r_0 = (x_0, y_0, z_0)$ and V in equation (1), (2) for which the function $Q(r_0, V)$ reaches a global minimum in the ranges of possible values of the microseismic source coordinates and medium equivalent velocity.

According to time difference location principles, the equation for calculation of the source origin time t_0 has the following form

$$\min_{t_0} F(t_0) = \min_{t_0} \sum_{i=1}^{n} \left(t'_i - t_0 - \frac{l_i(\hat{r}_0)}{\hat{V}} \right)^2, \tag{3}$$

In the equation, t'_i denotes the measured travel times; For a case where signal-to-noise ratios in observed signals from microseismic source are sufficiently high and earth medium between the source and geophones are homogeneous $\min_{r_0} F(t_0) \approx 0$ and estimate of the microseism origin time can be calculated as:

$$\hat{t}_0 \approx \frac{1}{n} \sum_{i=1}^{n} \left(t'_i - \frac{l_i(\hat{r}_0)}{\hat{V}} \right). \tag{4}$$

In solving for the seismic source location and origin time, the estimates of source coordinates $\hat{r}_0 = (\hat{x}_0, \hat{y}_0, \hat{z}_0)$ and the equivalent wave velocity $\hat{V}$ are obtained first according to equation (2). Then, the estimate of the origin time to is determined by substituting the estimated values $\hat{r}_0$ and $\hat{V}$ into equation (3) (or in equation (4) for the case where

$\min_{r_0} F(t_0) \approx 0$). Because equation (2) is a nonnegative function of (x_0, y_0, z_0) and V, a minimum $\min_{r_0,V} Q(r_0,V)$ always exists and can be found by the nonlinear fitting methods. The classic method is the "minimum least square solution" . However, in this solution_the source location estimate $\hat{r}_0$ correlates with the origin time estimate $\hat{t}_0$, and the algorithm has a slow convergence for the velocity V. It is easy also to get a non-uniquesolution (Chen et al., 2009). To overcome these problems, this paper introduces an adaptive PSO algorithm to optimize the solution process.

Source location based on time difference principle is a multi-extremum non-linear problem. The most popular method is the classical method proposed by Geiger (1912) and various improvements thereafter . This kind of method is a solution method in the linear category. That is to say, according to Taylor's formula, the non-linear problem is transformed into a linear problem, and then different strategies are adopted to solve the linear equation system. In many cases, such as second order or more will appear. Problems such as in appropriate omitting of terms, unreasonable selection of initial values, and trapping solutions into local minima will occur (Lee and Stewart, 1981). The Particle Swarm Optimization (PSO) method is simple to operate, easy to use, and easy to get the global optimal solution for multi-extremum non-linear problems. Therefore, the improved PSO method is introduced to solve the above problems.

3. Adaptive PSO algorithm forsolving location parameters

3.1 PSO principle

The PSO is an evolutionary computation technique developed by Eberhart and Kennedy (1995). It is an evolutionary algorithm similar to a simulated annealing optimization algorithm for a problem of iterative improving a candidate for the solution with regard to a given measure of quality. PSO is an intelligent computational algorithm for analyzing the dynamic behavior of a swarm of particles. In comparison with other similar algorithms PSO has such advantages as simple implementation, high accuracy and fast convergence. It has been successfully applied in the field of optimization in recent years (Fong et al., 2016; Renaudineau et al., 2015; Sudheeret al., 2014). The basic PSO principles are as follows: PSO randomly initializes a set of particles in the solution space. Each particle flies through the solution space with a certain speed by following the current optimum particle and the optimal solution is found through the search in successive generations. In each generation, the particles update themselves by tracking two types of extreme values: local optimums and global optimum. First extreme values are the optimal values for every particle itself in a set of positions of this particle in the sequence of already existing generations. They are denoted as *pBest*. Second optimum is the optimal value found in the all existing generations of the whole swarm of particles. It is denoted as *gBest*. After the two sorts of the optimal values are found, the particles update their speed and positions according to equation (5):

$$\begin{cases} v_{i,d}^{(k+1)} = w^{(k)} v_{i,d}^{(k)} + c_1^{(k)} r_1 (p_{i,d}^{(k)} - x_{i,d}^{(k)}) + c_2^{(k)} r_2 (p_{g,d}^{(k)} - x_{i,d}^{(k)}) \\ x_{i,d}^{(k+1)} = x_{i,d}^{(k)} + v_{i,d}^{(k+1)}, i = (1,\ldots,n), d = (1,\ldots,m) \end{cases}, \quad (5)$$

where m is the dimension of the particle space; n is a number of particles in the swarm; k is a number of the current evolutionary particle generation; r_1 and r_2 are independent random values within [0, 1]; $w^{(k)}$ is the inertia weight at the k-th particle generation; $c_1^{(k)}$ and $c_2^{(k)}$ are acceleration constants at the k-th particle generation; $v_{i,d}^{(k)}$ is the current flight speed for d-th component of i-th particle at the k-th generation; $x_{i,d}^{(k)}$ is the d-th component of i-th particle current location at the k-th generation; $p_{i,d}^{(k)}$ is the d-th coordinate of current optimal value for i-th particle itself at the k-th generation; $p_{g,d}^{(k)}$ is the d-th component of current optimal value for total particle population up to the k-th generation.

3.2 The algorithm for solving source location parameters

The equation (2) concerns a nonlinear optimization problems with multiple local extremums. The PSO algorithm was developed for solving such problems and can be applied to search for the optimal value in four-dimensional solution space composed of (x, y, z, v), that is, to solve for the source location and the equivalent seismic velocity. x, y, z and v is the 1-th, 2-th, 3-th and 4-th componnent of particles, respectively. The flowchart for the PSO algorithm is shown in Fig. 1.

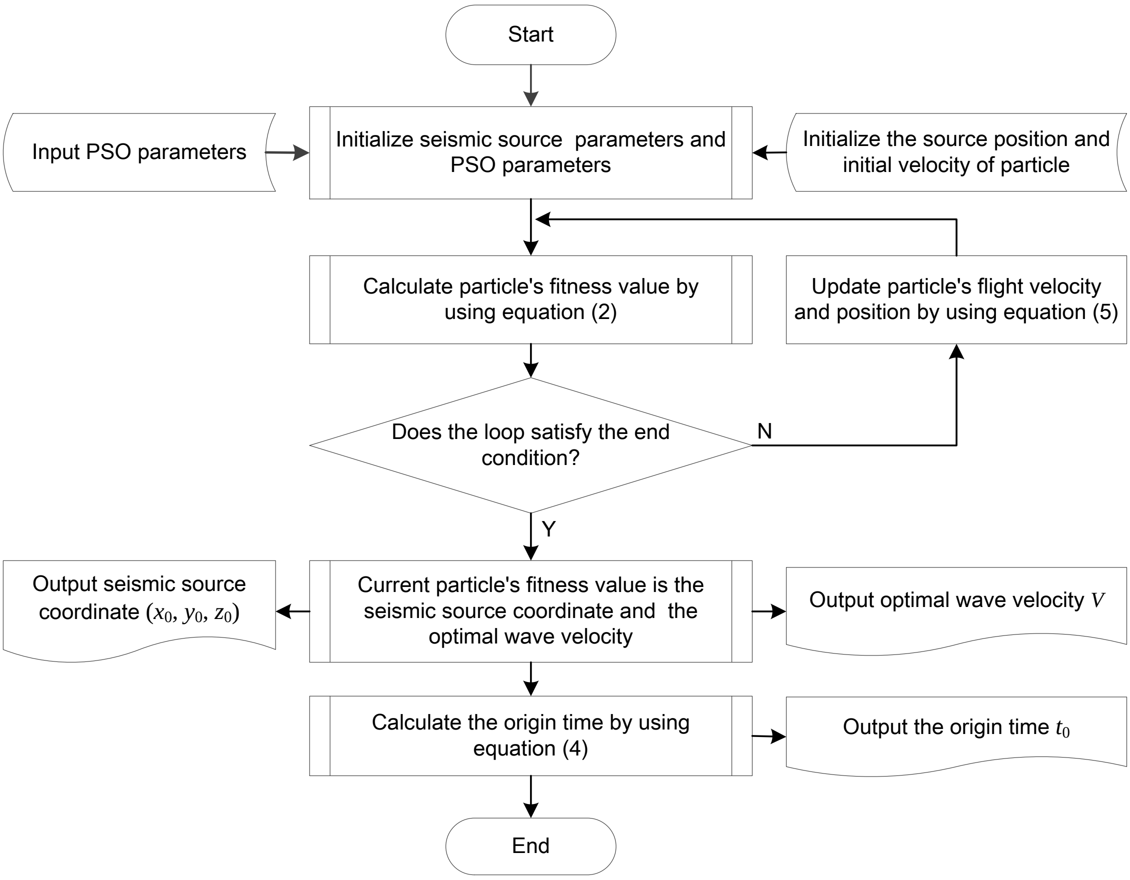


Fig. 1 Flowchart for the microseismic source location algorithm based on adaptive particle swarm optimization

The procedure for the source location parameter evaluation based on the PSO algorithm is described as follows:

Step1: Initialize the model parameters for microseismic source location and the PSO parameters. Randomly initialize the source position and wave velocity of PSO algorithm. Initialization of the PSO parameters mainly includes the population size m, acceleration constants c_1 and c_2, inertia weight w, computional accuracy ε, largest number of evolutionary generation $T_{\max}$, initial velocity and positions of the particles, and maximum particles flight speed $v_{\max}$. Then, initialize the iterative counter k.

Step2: Calculate particle's (microseismic source coordinate and velocity model) fitness value by using equation (2). The calculated values here are the source's 3-dimensional coordinates $\left(x_0^{(k)}, y_0^{(k)}, z_0^{(k)}\right)$ and equivalent velocity $V^{(k)}$, where k is the evolutionary generation number.

Step3: Judge whether the current parameters of the particles meets the presupposed flight times and positioning accuracy or not. If it does, then go to Step 5; otherwise, go to Step 4.

Step4: Update the flight velocity and particle positions according to equation (5), and then, goback to Step 2.

Step5: Output the estimated source's 3-dimensional coordinates $\left(\hat{x}_0, \hat{y}_0, \hat{z}_0\right)$ and equivalent wave velocity $\hat{V}$.

Step6: Calculate and output the origin time estimate $\hat{t}_0$ by substituting estimated values of the source coordinates $\left(\hat{x}_0, \hat{y}_0, \hat{z}_0\right)$ and equivalent velocity $\hat{V}$ into equation (4). When the solution for the source coordinates and the origin time are obtained, the algorithm is over.

3.3 Discussion of PSO algorithm parameters

The parameter values for the PSO algorithm are the keys to influence the algorithm performance and efficiency. This paper proposes guiding principles for adjusting parameters of the PSO algorithm based on the practical approach to solving for the seismic source parameters.

(1) Inertia weight $w^{(k)}$~~:~~

Generally, optimization problems are divided into local ~~optimum~~ and global problems~~optimum~~. The former consists in looking for the minimum~~Local optimum is to find the minimum~~ in a finite area of function value space, ~~while global optimum~~the latter is to find the minimum in the whole area of function value space. As early as 1998, Shi and Eberhart (1998) found that when the value of inertia weight w is relatively large, the global optimization ability of the PSO algorithm is strong, while the local optimization ability is weak. On the other hand, when the value of inertia weight w is relatively small, the local optimization ability of the PSO algorithm is strong, while the global optimization ability is weak. To avoid particles being stuck in a local optimum untimely or missing the global optimal solution, this study uses the strategy of self-adaptive inertia weight to determine the proper value of w (Zhang and Liao, 2009). The strategy is the following:

In order to enhance the exploring competence of the PSO algorithm, the population average velocity should be maintained rather high at the initial stages of evolution, while in the late stage of evolution a smaller population average velocity should be maintained in order to strengthen the development capabilities of the algorithm. We assume that evolution of the average particle flying velocity with changing number of generations k should be close to function defined by equation (6).

$$\bar{v}_{avg}^{(k)} = v_e^{(k)} = v_0 e^{-\left(\frac{2k}{T_{\max} - T_1}\right)^2}, \tag{6}$$

where v_0 represents the initial average velocity of population; T_{max} is the largest number of evolutionary generations; T_1 is the ~~initial value~~number of evolved ~~utionary~~ generations.

We will call $v_e^{(k)}$ as expected value of the average flying velocity for a particle population at k-th generation. The actual average velocity of the particle swarm at k-th generation is given by equation (7):

$$v_{avg}^{(k)} = \frac{1}{m}\sum_{i=1}^{m}\sqrt{\sum_{d=1}^{4}(v_{i,d}^{(k)})^2}, \tag{7}$$

Where $v_{i,d}^{(k)}$ represents the velocity of d-th component of the i-th particle at k-th generation.

Assign the initial inertia weight as w. Designate $w^{(k)}$ inertia weight for the k-th particle generation. Then the inertia weight $w^{(k+1)}$ for (k+l)-th generation is determined by equation (8):

$$\begin{cases} \text{if } v_{avg}^{(k)} > v_e^{(k)} \text{ then } w(k+1) = w(k)/p \\ \text{if } v_{avg}^{(k)} < v_e^{(k)} \text{ then } w(k+1) = w(k)\cdot p \\ \text{if } v_{avg}^{(k)} = v_e^{(k)} \text{ then } w(k+1) = w(k) \\ \text{if } w(k+1) > w_{\max} \text{ then } w(k+1) = w_{\max} \\ \text{if } w(k+1) < w_{\min} \text{ then } w(k+1) = w_{\min} \end{cases}, \tag{8}$$

where p is a some constant. Practice has proved that the best value of p is 1.05 (Zhang and Liao, 2009).

Substitution of $w^{(k)}$ given by equation (8) into equation (5) ensures that average velocity $v_{avg}^{(k)}$ will reduce to zero in the process of population evolution.

(2) Acceleration constants $c_1^{(k)}$ and $c_2^{(k)}$~~:~~

Gao and Liao noted that the position $x_{i,d}^{(k)}$ of each particle in the population eventually converges to $(c_1 p_{i,d} + c_2 p_{g,d})/(c_1 + c_2)$ (Gao and Liao, 2012), This means that the position of the particles for large k will stay close to the lines that connect the global optimum point with the local optimum point. Therefore, in the first stage of particle swarm optimization, the optimum value of the particle itself is an important parameter to make all particles converge to global optimum.

However, if $c_1^{(k)}$ would be high for all k then the optimum position of the particle swarm would, generally, not coincide with the global optimum of the target function (2). Therefore, at the first stage of PSO, $c_1^{(k)}$ should take a larger value, while $c_2^{(k)}$ should take a smaller value to promote the local optimization speed. When particle swarm optimization is near to its end, the role of the global optimal value should be highlighted. At this stage, $c_1^{(k)}$ should take a smaller value, while $c_2^{(k)}$ should take a larger value to help the particle swarm converge to the global optimum. Therefore, the acceleration constants $c_1^{(k)}$ and $c_2^{(k)}$ should be designed based on the average velocity of the particle swarm:

$$c_1^{(k)} = C\frac{v_{avg}^{(k)}}{v_{\max}}, c_2^{(k)} = C\left(1-\frac{v_{avg}^{(k)}}{v_{\max}}\right). \tag{9}$$

C is a a positive integer, usually in the range [2,5].

(3) The maximum flight velocity of particles $v_{\max}$~~:~~

The selection and analysis of the maximum flight velocity of particles should proceed as follows: if $v_{\max}$ is too small, then the particle movement will be restricted. In this situation, the algorithm cannot converge fast enough and may not even be able to achieve the optimal solution. On the other hand, if $v_{\max}$ is too large, then the optimal solution may be missed (Eslami et al., 2014; Abido 2002). Therefore, it is very important to dynamically adjust the $v_{\max}$ value.~~In this study, the $v_{\max}$ value is obtained as follows~~ To ensure uniform velocity through all dimensions, the maximum velocity in the *d*-th dimension is proposed as :

$$v_{\max,d} = \frac{x_{\max,d} - x_{\min,d}}{N}, \tag{10}$$

Where $x_{\max,d}$ and $x_{\min,d}$, respectively, stand for the largest and smallest values in the *d*-th dimension of the possible particle positions, and ~~the number of intervals in each space dimension~~ N is a chosen number of intervals (Abido 2002), usually in the range [1, 10].~~are selected as 1.0 and 10 respectively.~~

4. Simulation and case study

4.1. Simulation analysis and discussion

For the simulation, eight sensors comprising a microseismic localization system are located on the eight vertices of a cube. Four microseismic sources,O, P, Q, ~~S,~~ etc., are located inside the cube, and R is located outside the cube. The coordinates of the geophones and the microseismic sources are shown in Table 1, and the relative locations of the geophones and microseismic sources are shown in Fig. 2.

Table 1 Coordinates of sensors and microseismic sources

Geophone coordinates(m)	Microseismic source coordinates(m)
A(0,0,0)	O(400,400,400)
B(800,0,0)	P(300,600,700)
C(800,800,0)	Q(300,200,300)
D(0,800,0)	R(500,600,1200)

E(0,0,800)
F(800,0,800)
G(800,800,800)
H(0,800,800)

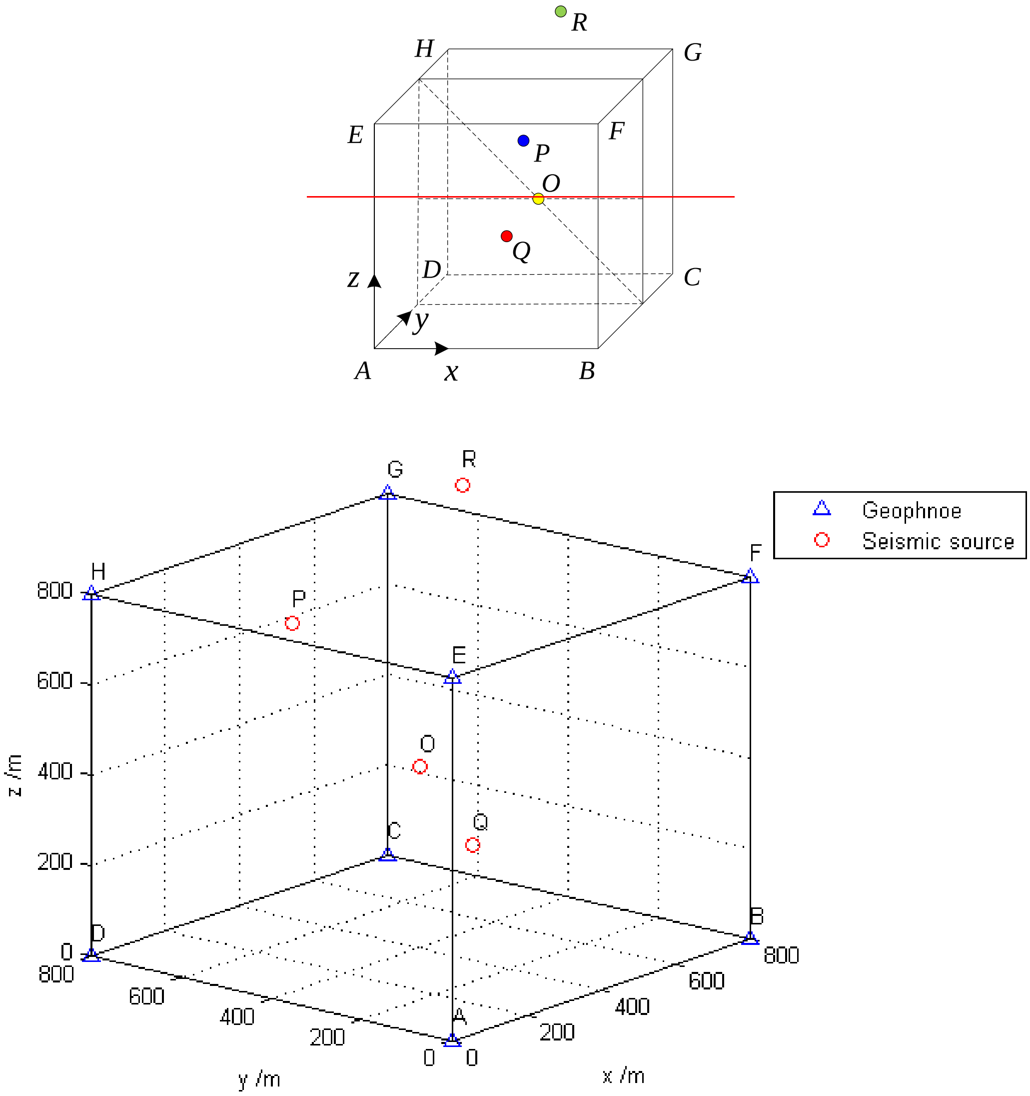


Fig. 2 The locations of geophones and microseismic sources

It is assumed that the velocity of wave propagation (v) in the medium is unknown. According to the coordinates of geophones and microseismic sources shown in Table 1, First, the synthetic travel ~~time t and origin time t_0 can be~~have been computed ~~calculated~~. Then, the differences between the arrival times at all the pairs of station have been retrieved according to ~~t and t_0 are substituted into~~ equations (2), (3) and (4), and inversion is carried out by the least squares method (Dong et al., 2011) and the PSO proposed in this paper. The microseismic source location, equivalent wave velocity, and origin time are obtained. Then, the results calculated using the two different methods are compared using error analysis, the algorithm execution time, and the number of iterations.

Suppose a microseismic velocity v=5.60m/ms. According to the coordinate information in Table 1, the trigger time of the microseismic waves recorded by the geophones triggered can be calculated, as shown in Table 2. For the convenience of discussion, we abbreviate the least square method as LSM, and the method in this paper is PSO. The computational accuracy of the LSM algorithm is ε=1.0×10^{-10}. The parameters for the PSO algorithm are as follows: population size m=50, w_0=1 and T_{max}=3000. The inertia weight w, acceleration constants c_1 and c_2 and maximum flight velocity of particles v_{avg} are determined by equations (6-10). MATLAB programming was used to implement the LSM and PSO algorithms to obtain solutions at four points O, P, Q and R. The calculated results are shown in Table 3. The results of convergence are different when different initial values are selected for LSM method. When the initial value is far from the true value, the LSM method satisfies the end condition, but it does not get the true value of the microseismic source. By repeatedly adjusting the initial value, the algorithm converges to the correct result. The corresponding initial values of LSM method in Table 3 are obtained after several adjustments. The PSO method can converge to the true value only by randomly selecting a set of initial values within a specified range.

Table 2 Travel time of a microseismic wave

Geophones	Travel time(ms)			
	O	P	Q	R
A	123.72	173.13	83.76	255.68
B	123.72	187.29	110.08	245.50
C	123.72	157.71	149.40	223.75
D	123.72	140.61	131.22	234.87
E	123.72	121.11	110.08	156.70
F	123.72	140.61	131.22	139.47
G	123.72	97.81	165.60	96.16
H	123.72	66.82	149.40	119.79

Table 3 Comparison of the LSM and PSO algorithms

Algorithm		Microseismic source O				
		x(m)	y(m)	z(m)	t_0(ms)	v(m/ms)
LSM	Initial value	350.00	350.00	350.00	0.00	1.00
	Calculatedvalue	400.00	400.00	400.00	-	-
PSO	Initial value	0~800	0~800	0~800		0~10
	Calculatedvalue	400.00	400.00	400.00	-	-
True value		400.00	400.00	400.00	0.00	5.60
Algorithm		Microseismic source P				
		x(m)	y(m)	z(m)	t_0(ms)	v(m/ms)
LSM	Initial value	100.00	400.00	500.00	0.00	1.00
	Calculatedvalue	304.37	295.22	703.63	6.27	5.85
PSO	Initial value	0~800	0~800	0~800		0~10
	Calculatedvalue	301.23	298.95	701.02	1.81	5.67
True value		300.00	300.00	700.00	0.00	5.60
Algorithm		Microseismic source Q				
		x(m)	y(m)	z(m)	t_0(ms)	v(m/ms)
LSM	Initial value	100.00	100.00	100.00	0.00	1.00

	Calculatedvalue	263.98	206.33	304.59	2.92	5.81
PSO	Initial value	0~800	0~800	0~800		0~10
	Calculatedvalue	258.84	201.35	298.01	1.11	5.68
True value		260.00	200.00	300.00	0.00	5.60
Algorithm		Microseismic source R				
		x(m)	y(m)	z(m)	t_0(ms)	v(m/ms)
LSM	Initial value	300.00	400.00	1000.00	0.00	1.00
	Calculatedvalue	491.28	590.68	1208.32	13.82	5.92
PSO	Initial value	0~800	0~800	0~800		0~10
	Calculatedvalue	504.21	605.23	1195.25	4.48	5.70
True value		500.00	600.00	1200.00	0.00	5.60

Notes: “-” means that the value cannot be obtained directly; the calculatedvaluefrom the PSO is the average value obtained after running the PSO algorithm twenty times.

Based on the results shown in Table 3, the LSM algorithm has different convergent results for different initial values. When the initial value is far from the true value, the required calculation accuracy ε can be met, but the result does not approach the true value. In some cases, there are multi-group results, so the initial values need to be repeatedly adjusted in order to make the LSM algorithm approach the true value. For the PSO algorithm, a wide range of initial values was used for the microseismic source location parameters. The only variables that need to be solved for are the 3-dimensional coordinates of the arbitrary point inside the space surrounded by the seismic detection equipment. Thus, the calculated results can better approach the true value, and the solution is unique. This occurs because by improving the parameter selection rules, the condition that particles are trapped in local optima or fly over the global optimum during the process of searching is avoided; thus, the optimization ability of the PSO algorithm is improved.

Comparisons of the errors in the microseismic source location parameters obtained using the LSM and PSO algorithms are shown in Fig.3, and the comparison of iterations between the two algorithms is shown in Fig.4.

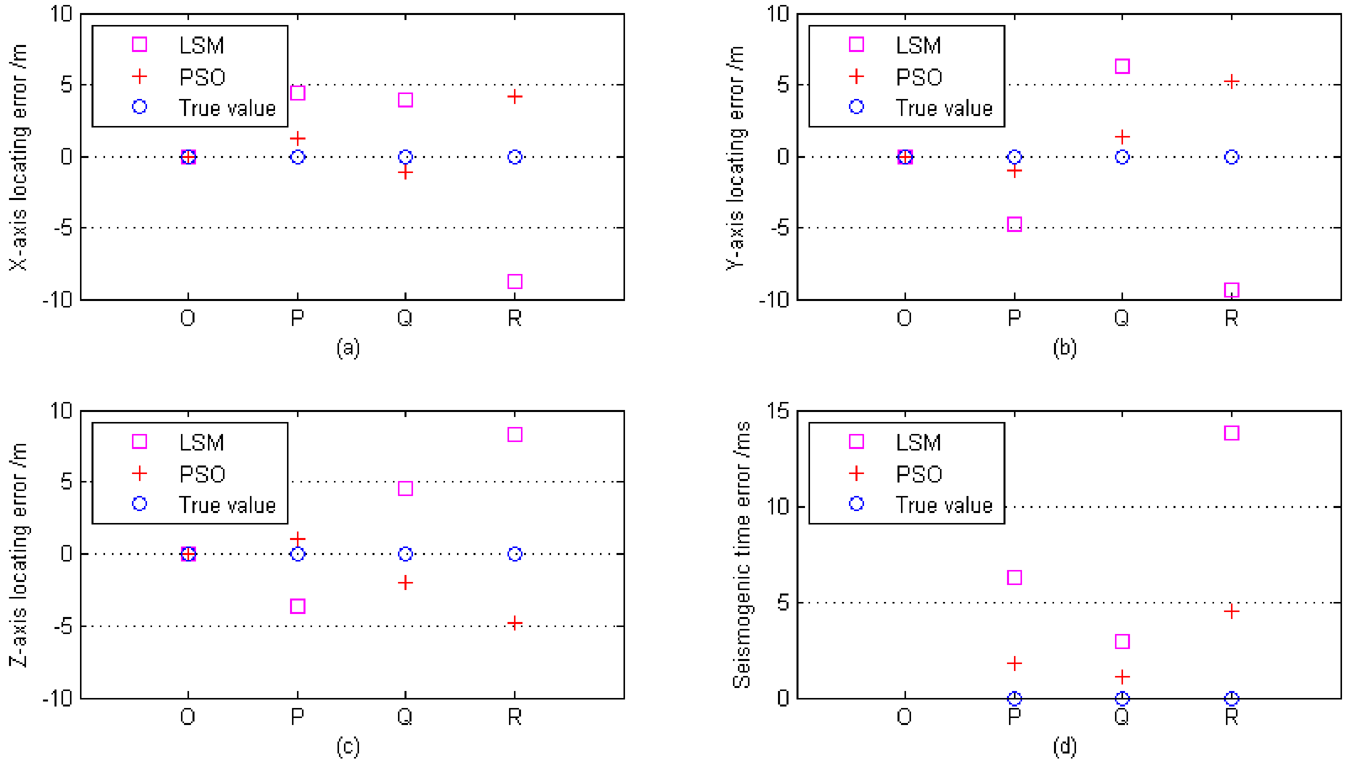
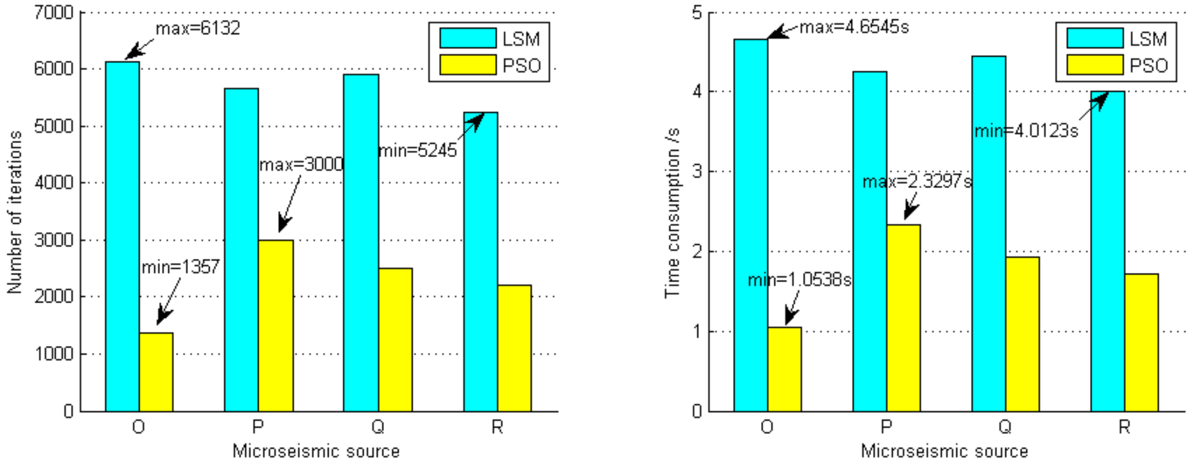


Fig. 3 Comparisons of the errors in the source location parameters between the LSM and PSO algorithms: (a) Comparisons of the x-axis locating error; (b) Comparisons of the y-axis locating error; (c) Comparisons of the z-axis locating error; (d) Comparisons of the errors in the origin time estimation.



(a) (b)

Fig. 4 (a) Comparison of the number of iterationsbetween the LSM and PSO algorithms, wherethe max and min markers are highlighting the max and min number of iterations for each algorithm; (b) Comparison of the computing time between the LSM and PSO algorithms, wherethe max and min markers are highlighting the max and min amount of computing time for each algorithm.

The selection of initial values for parameters in the LSM algorithm is comparatively complex, so the basic principle of parameter selection is to approach the desired value as near as possible. The selection of different initial values for parameters in the LSM algorithm has a greater influence on the accuracy of the solution location compared to PSO and results in a large difference in the number of iterations between the two methods. The improved PSO algorithm only needs to be provided a value range for the initial parameters. Then, it automatically selects parameter values to iterate, and the algorithm runs for a maximum number of 3000 iterations. As is shown in Table 3, Fig.3, and Fig.4, compared with the LSM algorithm, the PSO algorithm not only improves the computational accuracy of the desired value of microseismic source parameters but also increases the computational efficiency and determines the microseismic source's real-time location.

The following is a discussion of some special conditions. 1) Since source O is located at the cube's center of gravity, the distance between O and each geophone is the same. As a result, both the LSM and PSO algorithms can converge to the true value when solving for the seismic source coordinates (x_0, y_0, z_0) but cannot solve the origin time t_0 because regardless of which value of wave velocity v isselected, the value of Q in equation (2) tends to be zero. Because of the randomness of the wave velocity, the origin time t_0 cannot be solved according to equation (3). 2) Since source R is located outside the cube, The average distance from this point to each sensor is larger than that from other points in the cube, such as P and Q points, to each sensor.. The error in the equivalent wave velocity, which is solved by iteration, causes greater location error for R than for other points in the cube, so the layout of the seismic detection equipment should ensure that the microseismic source is within the detection array.

4.2 Case study

Because rock burst occurs frequently at a mine in central China, a Paladin 24-bit, multi-channel microseismic monitoring system of the ESG Company in Canada was installed. In total, 18 seismic detection devices are installed in different positions at the mine, 9 seismic detection devices are installed at the -520 level and 9 at the -840 level. A blasting operation with known position was conducted in order to verify the validity of the PSO algorithm. Ten seismic detection devices detected microseismic signals during the blasting operation. Pre-treatments of the data, such as denoising and filtering, were performed on the detected signals in order to obtain a high SNR. Then, two blast points that showed an obvious rising waveform trend, making it easy to capture the trigger time, were selected and analyzed. The position coordinates of the two points are A(1495.60, 998.50, -685.10) and B(1298.70, 855.30, -576.20). The coordinates of the 10 seismic detection devices and the trigger times detected are shown in Table 4. The relative position of the 10 geophones and the 2 burst points is shown in Fig. 5. The seismic waveform data received by the geophone are shown in Fig. 6.

Table 4 Geophone coordinates and travel time from the burst point

Geophone No.	Geophone Coordinates (m)			Travel time(ms)	
	x	*y*	*z*	Burst point A	Burst point B
2#	751.26	549.55	-520.51	157.39	112.01
3#	755.40	1302.64	-523.35	146.02	146.02
4#	1752.37	700.70	-519.43	76.08	86.03
6#	2005.65	1298.72	-521.35	109.69	149.34
9#	1512.59	1149.63	-519.15	39.98	65.41
12#	995.87	1305.66	-820.20	107.27	106.07
13#	1248.20	1597.85	-821.95	118.96	140.72
15#	1500.46	550.75	-819.87	82.76	77.72

16#	2254.38	1303.22	-818.35	146.92	192.00
17#	1750.34	998.48	-822.73	52.20	96.23

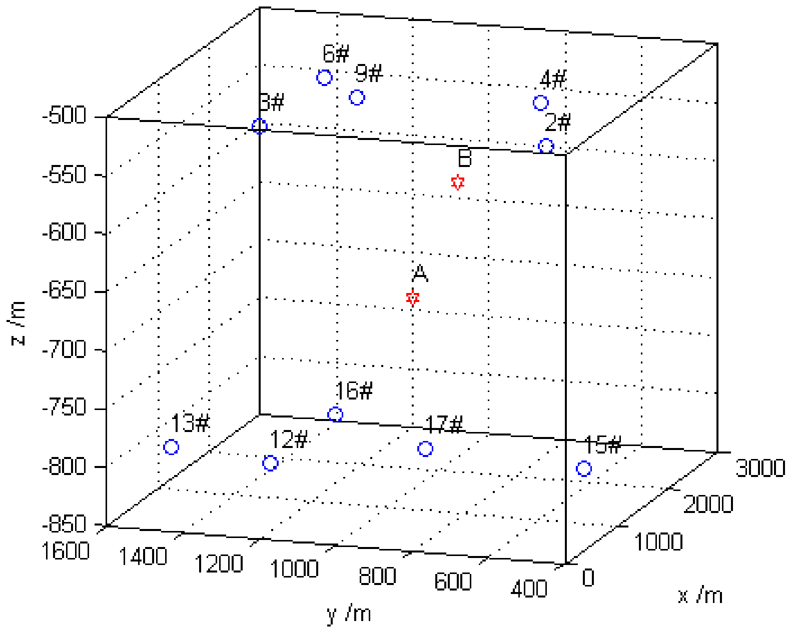


Fig. 5 Schematic diagram of the relative position of the 10 geophones and the 2 burst points

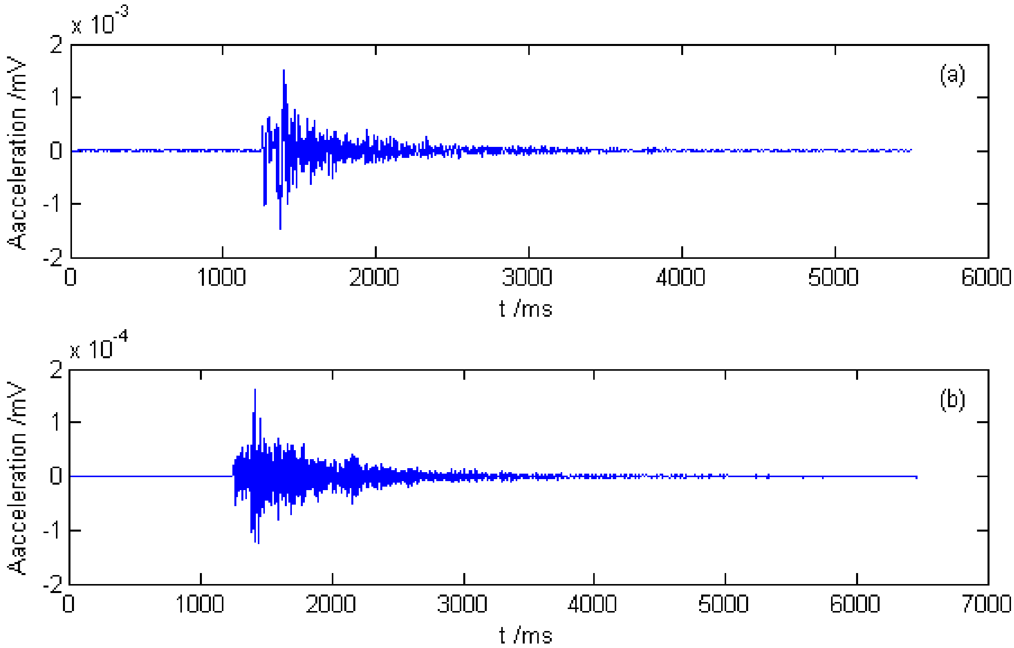


Fig. 6 (a) Seismic waveform of burst point A received by geophone 2#; (b) Seismic waveform of burst point B received by geophone 2#

The experiment was carried out in the advance roadway of the coal mine working face. The diameter of the borehole is 42 mm, the depth of the borehole is 1.2 m, and the length of the filled explosive is 1/4 of the borehole depth. We approximate the blasting point to a spherical blasting point without considering the error caused by the assumption. Based on the data presented in Table 4, the PSO algorithm and LSM algorithm were used to solve for the seismic source location parameters and origin time. A comparison of the error is shown in Table 5.

Table 5 Error comparison for the LSM algorithm and PSO algorithm

		X_{err}(m)	Y_{err}(m)	Z_{err}(m)	T_{err}(ms)
Burst point A	LSM	9.65	10.39	13.05	18.63
	PSO	6.78	5.27	9.79	10.33
Burst point B	LSM	8.28	11.22	12.74	27.24
	PSO	5.96	6.29	8.26	15.95
Error	LSM	8.97	10.81	12.90	22.94
	PSO	6.37	5.78	9.03	13.14

According to Table 5, the accuracy of the LSM algorithm is relatively poor. Its average deviation in the X, Y and Z directions are 8.97m, 10.81m and 12.90m. The results were obtained after repeated adjustment of the initial location parameters for the seismic source and the wave velocity. The PSO algorithm can automatically approach the true values according to the given initial parameter range. Its average deviation in the X, Y and Z directions are 6.37m, 5.78m and 9.03m, with errors that are less than 5%. Therefore, the PSO can achieve high positioning accuracy in the geophone array range.

The simulation example and blasting experiment discussed above clearly demonstrate that the PSO optimization algorithm is better than LSM when solving for the microseismic positioning parameters and the seismic origin time. The algorithm has high positioning accuracy and fast convergence speed, and it is easy to set the initial parameters. This is because the adaptive PSO algorithm is more accurate in fitting the relationship between each coordinateforthe seismic detection equipment and the time difference. It can dynamically adjust the velocity value in an iterative process until the value approximates the optimal average velocity, which can account for the nonlinear relationship between each coordinate of the seismic detection equipment and the time difference and can greatly reduce the impact of the velocity error on the positioning precision.

4.3 Discussion

In order to further verify the effectiveness of the proposed method, the experiments in Section 4.1 are compared and analyzed under different wave velocities. The comparative analysis steps are as follows: (1) Using PSO method and LSM method to locate microseismic source when using real velocity (i.e. error floating 0%); (2) Because it is difficult to measure real wave velocityin practical engineering, a small errors of 1%, 3% and5% is given to the PSO method and LSM method respectively, that is, when the wave velocityis 5.544, 5.432 and 5.320m/ms,two methods are used to locate the microseismic source;(3) Steps (1), (2) are used to locate the microseismic source, and the absolute distance error is calculated by comparing the locating results with the real values. The absolute distance errors calculated by the PSO method and the LSM method at different wave velocities are plotted in Fig. 67.

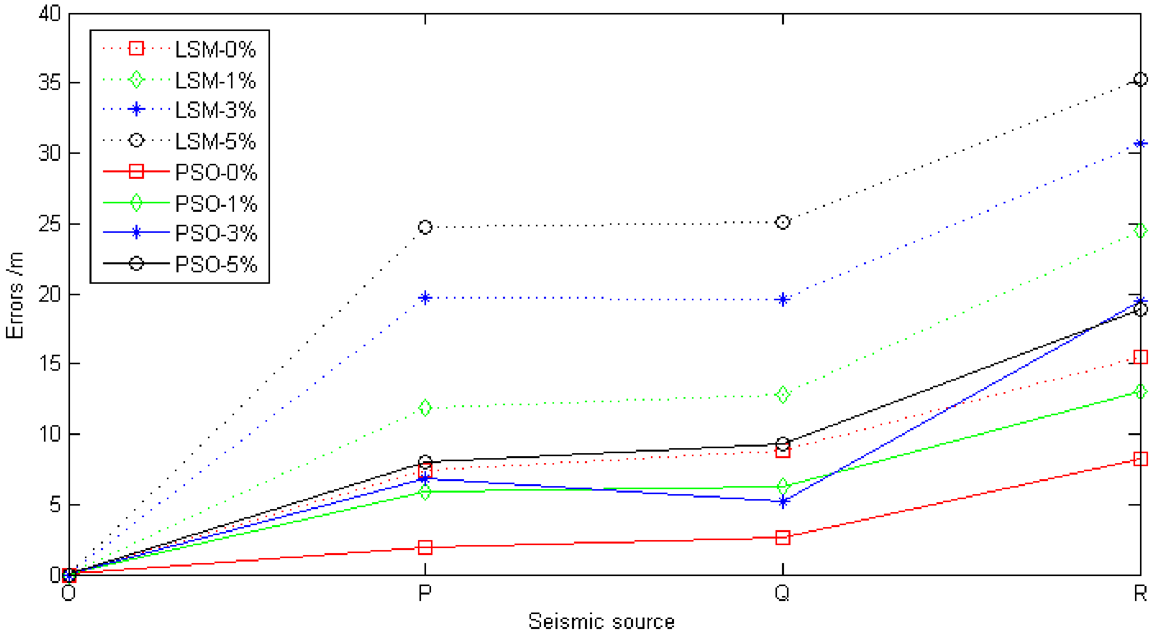


Fig. 6 7 Comparison of locating errors between PSO method and LSM method at different wave velocities

As we can be seen from Fig. 67, the LSM method will cause large errors in the location system under the disturbance of different wave velocities. The maximum error is up to 25m (Except for the seismic source R), while the PSO method is more stable. The reason is that the PSO method can accurately fit the relationship between the coordinates of each sensor and the time difference, because it does not depend on the velocity value when solving the seismic location parameters. The LSM method needs accurate velocity to solve the seismic location parameters, and the disturbance of velocity has a great influence on the results. That is to say, in the case of wave velocity disturbance, even if there is a small error in the value of wave velocity, there will be a large error in the location result of LSM method. Because of the complexity of rock media, the average velocity of each region is not necessarily the same, and the influence of construction technology, it is very difficult to determine the velocity of anisotropic media, which is the main reason for the low positioning accuracy of LSM method. In addition, when the source is outside the sensor array (Such as seismic source R), the errors of the two methods are very large, but the LSM method has greater locating errors than PSO method, which shows that the sensor arrangement should ensure that the seismic source is within the array as far as possible.

5. Conclusions

(1) An adaptive PSO optimization method is proposed based on the average population velocity in order to solve for location parameters of the seismic source in a location model. This method takes the minimum residual sum of squares between the time difference regression values and the time difference measured values for two seismic detection devices, and the PSO algorithm is designed to solve for the seismic source coordinates and the equivalent wave velocity and then solve for the seismic source origin time.

(2) Combined with the actual need to solve for seismic source parameters, the model constraints of inertia weight, accelerating constants, the maximum flight velocity of particles, and other parameters are discussed in order to improve the optimization capacity of the PSO algorithm and avoid being trapped in a local optimum.

(3) Comparative analysis shows that when solving for the seismic source location parameters, compared with the classic least squares method, the adaptive PSO algorithm has high positioning accuracy and fast convergence, and it is easy to set the initial parameter values.

Acknowledgments

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References

Abido M. A. Optimal power flow using particle swarm optimization.Int. J. Electr. Power Energy Syst.,24(7), 563-571, 2002.

Anikiev D., Valenta J., Staněk F., et al. Joint location and source mechanism inversion of microseismic events: benchmarking on seismicity induced by hydraulic fracturing.Geophys. J. Int.,198(1), 249-258, 2014.

Feng, G. L., Feng, X. T., Chen, B. R., et al. Sectional velocity model for microseismic source location in tunnels. Tunn.Undergr. Sp. Tech., 45, 73-83, 2015.

Dong L., Li X. A microseismic/acoustic emission source location method using arrival times of ps waves for unknown velocity system.Int. J. Distrib. Sens. Netw.,2013(3), 485-503, 2013.

Dong, L., Sun, D., Li, X., & Du, K. Theoretical and experimental studies of localization methodology for ae and microseismic sources without pre-measured wave velocity in mines. IEEE Access, 99, 16818-16828, 2017...

Eberhart R C, Kennedy J. A new optimizer using particle swarm theory. Proceedings of the Sixth International Symposium on Micro Machine and Human Science, Nagora, Japan, 39-43, 1995.

Eslami M., Shareef H., Taha M. R., et al. Adaptive particle swarm optimization for simultaneous design of upfc damping controllers. Int. J. Electr. Power Energy Syst.,57(5), 116–128, 2014.

Fong S., Wong R., Vasilakos A. Accelerated pso swarm search feature selection for data stream mining big data. IEEE Trans. Serv. Comput.,9(1), 33-45, 2016.

Gao Z., Liao X. Z. Hybrid adaptive particle swarm optimization based on average velocity. Control Decis.,27(1), 376-381, 2012.

Geiger L. Probability method for the determination of earthquake epicenters from arrival time only. Bull. St. Louis. Univ., 8, 60-71, 1912.

Gong S. Y., Dou L. M., Ma X. P., et al. Study on the construction and solution technique of anisotropic velocity model in the location of coal mine tremor.Chinese J. Geophys.-Chinese Ed.,55(5), 1757-1763, 2012.

Lee W H K, Stewart S W.Principles and applications of microearthquake networks. New York: Academic Press, 1981.

Jia R. S., Liu C., Sun H. M., et al. A situation assessment method for rock burst based on multi-agent information fusion.Comput. Electr. Eng.,45, 22-32, 2015.

Li N., Wang E., Ge M., et al. A nonlinear microseismic source location method based on simplex method and its residual analysis.Arab. J. Geosci.,7(11), 4477-4486, 2014.

Li X., Wang E., Li Z., Liu, Z., et al. Rock burst monitoring by integrated microseismic and electromagnetic radiation methods.Rock Mech. Rock Eng.,49, 1-14, 2016.

Lienert B R, Berge E, Frazer L.N. Hypocenter: an earthquake location method using centered, scaled, and adaptively damped least squares. Bull. Seismol. Soc. Amer., 6(3), 771-783, 1986.

Lin F., Li S. L., Xue Y. L., et al. Microseismic sources location methods based on different initial values.Chin. J. Rock Mech. Eng.,29(5), 996-1002, 2010.

Lomax A., J. Virieux, P. Volant and C. Berge, Probabilistic earthquake location in 3D and layered models: Introduction of a Metropolis-Gibbs method and comparison with linear locations, in Advances in Seismic Event Location Thurber, C.H., and N. Rabinowitz (eds.), Kluwer, Amsterdam, 101-134, 2000.

Lomax A., A. Zollo, P. Capuano, and J. Virieux, Precise, absolute earthquake location under Somma-Vesuvius volcano using a new 3D velocity model, Gephys. J. Int., 146,313-331, 2001.

Nelson G D, Vidale J E. Earthquake locations by 3D finite difference travel times. Bull. Seismol. Soc. Amer., 80(2), 395-410, 1990.

Pastén D., Estay R., Comte D., et al. Multifractal analysis in mining microseismicity and its application to seismic hazard in mine. Int. J. Rock Mech. Min. Sci., 78, 74-78, 2015.

Prange M. D., Bose S., Kodio O., et al. An information-theoretic approach to microseismic source location.Geophys. J. Int.,201(1), 193-206, 2015.

Renaudineau H., Donatantonio F., Fontchastagner J., et al. A pso-based global mppt technique for distributed PV power generation.IEEE Trans. Ind. Electron.,62(2), 1047-1058, 2015.

Shi Y., Eberhart R. C. Parameter selection in particle swarm optimization. Evolutionary Programming VII. Springer Berlin Heidelberg, 1998.

Sudheer C., Maheswaran R., Panigrahi B. K., et al. A hybrid svm-pso model for forecasting monthly streamflow.Neural Comput. Appl.,24(6), 1381-1389, 2014.

Sun H. M., Jia R. S., Du Q. Q., et al. Cross-correlation analysis and time delay estimation of a homologous micro-seismic signal based on the Hilbert-Huang transform. Comput. Geosci., 91, 98-104, 2016.

Usher P. J., Angus D. A., Verdon J. P. Influence of a velocity model and source frequency on microseismic waveforms: some implications for microseismic locations.Geophys. Prospect., 61, 334–345, 2013.

Waldhauser F, Ellsworth W L. A double-difference earthquake location algorithm: method and application to the northern Hayward fault, California.Bull. Seismol. Soc. Amer.,90(6), 1353-1368, 2000.

Xue Q., Wang Y., Zhan Y., et al. An efficient gpu implementation for locating micro-seismic sources using 3d elastic wave time-reversal imaging.Comput. Geosci.,82, 89-97, 2015.

Zhang D. X., Liao R. Q. Adaptive particle swarm optimization algorithm based on population velocity.Control Decis.,24(8), 1257-1246, 2009.