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ScienceDirect

Trans. Nonferrous Met. Soc. China 26(2016) 2988–2996

Transactions of  
Nonferrous Metals  
Society of China

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## Relocation method of microseismic source in deep mines

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Received 22 September 2015; accepted 1 September 2016

**Abstract:** A new method, named relocation, was proposed to reduce the impact of sensor errors systematically, especially when available data of sensors are abundant. The procedure includes evaluating the reliability of every sensors datum, processing the initial location by the credible data, and selecting a set of equations with optimal noise tolerance according to the relative relationship between the initial location and sensors location, then calculating the final location by *k*-mean voting. The results obtained in this research include comparing traditional location method with the presented method in both simulation and field experiment. In the field experiment, the location error of relocation method reduced 41.8% compared with traditional location method. The results suggested that relocation method can improve the fault-tolerant performance significantly.

**Key words:** micro-seism; relocation; *k*-mean; equation selection; sensor array

## 1 Introduction

The first rock-burst may be observed in 1640 in Altenbergtin according to the relative record [1]. Since then, a large number of mines all over the world have subjected to adverse impacts from seisms. For example, Kladno Black Mine (Czech) has subjected to 273 mines seismic event from 1880 to 1894, and Kolar Gold Field (India), Sudbury Mine (Canada), and Witwatersrand Mine (South Africa) were also recorded to experience many seismic subsequently in the 1900s. Now, the world has seen the severe threat of mine seism such as rock destabilization, roof fracture, downfalls and displacements [2–4]. With the increase of mining depth in recent years, the number of severe mine seisms is growing rapidly. It may bring out economic losses, engineering damage, the gas and coal dust explosion, and even leads to casualties.

The microseismic (or acoustic emission) monitoring has been certified to be an effective way to real-timely, dynamically and continuously monitor the rock pressure situation, and predict the potential disasters. By monitoring wave signal (which is generated by rock

failure and recorded by sensors), analyzing and calculating the data and information of waveform, the seismic source location and time could be deduced. According to the principle of the source location, seismic source localization methods can be divided into two categories: one is based on three axis sensor, which is used in the earthquake and ultra-deep drilling operation commonly, as Fig. 1(a) shows; the other is based on the time delay of arrival (TDOA), as Fig. 1(b) shows, whose basic idea is to establish arrival-time equation, and solve the equation by a certain mathematical method (iterative method or non-iterative method), then get the source location and the original time.

The most commonly used source localization method is the second method (based on the difference of arrival time) [5,6]. It can be classified into the non-iterative solution [7,8] and the iterative solution [9] according to the mathematical method for solving TDOA function. The most classical iterative algorithm of source location is Geiger algorithm [9], which is proposed by Geiger in 1910. Then, some other researchers [10–14] have made some progress on simplifying the model and computer programs. This method and its modifications have been widely used till now. Then, joint epicenter

**Foundation item:** Projects (11472311, 41272304, 51504288) supported by the National Natural Science Foundation of China

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DOI: 10.1016/S1003-6326(16)64429-1

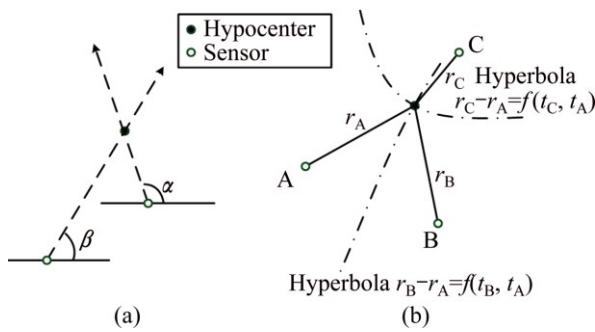


Fig. 1 Two kinds of seismic source location methods

determination method [15], relative positioning method (such as DDA[16]), nonlinear location method and the simple algorithm [17] have got a rapid develop, which have improved the precision and stability of location.

There are a lot of researches on the influence factors of location accuracy. The sensors array or the seismic networks station, the sensitivity and precision of sensors, the difference of arrival time (TDOA), wave velocity model and the source location algorithm are the key factors which influence the accuracy of seismic source localization. Regarding the error from wave velocity model: In the 1970s, the suppression-subtractive hybridization (SSH) method is proposed by CROSSLON [18], who makes speed as a variable in the source localization process, and calculates the source joint speed. It reduces the error to some extent because of the proposed speed model. But, the introduction of the unknown parameter will increase the amount of calculation and make the solving process not so stable. In 2008, LI and DONG [19,20] proposed a method without pre-measuring speed, significantly reduced the error result from velocity measurement. Also, they discussed the three-dimensional analytical solution of this problem [21,22]. In terms of the error due to microseism network, KIJKO [23,24] thought that microseism network has a significant effect on the source location accuracy, GONG et al [25] established genetic algorithm model for large-scale network planning problem by D value optimization theory; TANG et al [26] and JIA and LI [27] researched microseismic monitoring network optimal placement in deep metal mines and coal mines respectively [26,27]. LI [10] and GE [5,6] verified that with the increase of the distance between source and sensors, the location accuracy and stability are decreasing consistently and nonlinearly [10].

Considering the different importance of each sensor in location, the relocation method is proposed in this work. Here, the data of each sensor will be validated according to the probability and reliability of data, the erroneous data will be removed prior. And then the part

of some optimal equation groups will be picked out by the procedure of equations selection. The final location is considered to be the average result from all selected high-confidential equation groups.

## 2 Problem and motivation

Firstly, the problem description and the terminology of this paper will be given out. The goal of source location is getting the location of a microseism by sensor data. Assuming that the location of the source is  $(x, y, z)$ , it is an unknown variable, and it is the target of our research.  $t$  denotes the time when the microseism event generated. It is also unknown, but it can be gotten as long as the source location is known. The number of sensors is  $N$ , and the location of the  $i$ th sensor is  $(a_i, b_i, c_i)$  ( $i=1, 2, \dots, N$ ), this is known beforehand. The time when the microseismic wave arrived the  $i$ th sensor is  $t_i$ , which is known. And  $t_i - t_j$ , named time delay of arrival (TDOA for short), will be denoted as  $\tau_{ij}$ . The velocity of the waveform is  $v$ , which is a constant and can be measured beforehand. Then, the location of the source can be transform to a classical propagate problem in the homogeneous medium as follows.

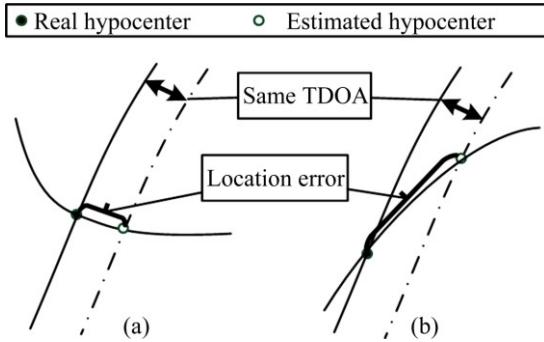
$$D_i = [(a_i - x)^2 + (b_i - y)^2 + (c_i - z)^2]^{1/2} = v(t_i - t) \quad (1)$$

It can be transformed by subtracting two equations (1) with different sensors  $i$  and  $j$  introduced.

$$D_i - D_j = v(t_i - t_j) \quad (2)$$

The location of microseism can be gotten from above equations if the number of sensors is greater than 4 in 3-dimensional space, or the number is greater than 3 in 2-dementional space. There are a lot of researches about how to solve the Eq. (2), such as Refs. [10,14,20]. In these traditional methods, nearly all sensors data are used to construct equation with the same weight value. This will inevitably introduce errors in the following two steps, so we specifically put forward two strategies to optimize the calculation results according to these two steps respectively. 1) Inappropriate data or failed sensors may bring in error. Some random factors may cause some abnormal data of sensors, for example, instability of circuit, field construction, system error or some human influence. These abnormal data would introduce considerable errors to the ultimate location. Therefore, they should be picked out and discarded before computing. 2) Inappropriate equations may amplify the measurement error. In practice, it can often be found that the error of location varies considerably when different sensor data are used. Figure 2 gives an example, where solid line is the original hyperbola without errors, and the dashed line is the hyperbola with noise. In two

subfigures of Fig. 2, TDOA is the same, but one of the hyperbola is different, and then the location error makes a significant difference. From the figure, we can find that the included angle of two hyperbolae in Fig. 2(a) is higher than that in Fig. 2(b).



**Fig. 2** Principle of sensors data effect on location precision: (a) Configuration 1; (b) Configuration 2

As Fig. 2 shows, if some inappropriate equation combinations are used in calculation, the sensor error will be amplified in the final location result. Therefore, we expect to choose the data with high reliability and the reasonable combination of equations with optimal noise tolerance to get the more accurate microseismic source location, in which, the data with high reliability could be selected according to the voting principle and propagation theory. In terms of the equation selection, is determined the approximate location of a micro source according to the traditional method, and equations with optimal noise tolerance are selected according to the relative position relationship between the source and sensors, then the exactly source location is gotten.

### 3 Model

Here we present a new method named relocation method to solve the select problem of the optimal sensors data and equation groups respectively.

#### 3.1 Voting method and constraint method

##### 3.1.1 Voting method

It is assumed that most of the sensor data are normal, while a little may be exceptional, i.e., with a high error. Then we can design a method which could identify those exceptional data by a voting mechanism and get a better location result. The voting method is described in Algorithm 1. Here, the location and TDOA of sensors are known. Then we will search all possible combination of four sensors (because four sensors are the minimum number of locating a source in 3-dimentional space) to get  $C(N, 4)$  different locations of the source, as step 1 shows. Then the  $k$ -mean method is used to find out a

reliable centre of those possible locations of the source. Here, reliable centre means that most of the locations are close to this point. If a location fixed by sensor  $S_1, S_2, S_3$  and  $S_4$  belongs to the biggest cluster, then the credit of  $S_1, S_2, S_3$  and  $S_4$  will increase respectively. The outstanding 80% sensors with higher credit value will be kept for future computation.

Input: Sensor location $(x_i, y_i, z_i)$ , TDOA $(t_{ij})$ , $(i, j=1, 2, \dots, N)$
Output: Source location $(a, b, c)$
Step 1: For any arbitrary selected 4 sensors, get a source location by solving equation group (2) with $(x_i, y_i, z_i)$ and $(t_{ij})$ . Then $M=C(N, 4)$ location can be gotten totally.
Step 2: Clustering $M$ location by $k$ -mean method with $K=2$ , and location similarity is defined as Euclid distance
Step 3: If radius of the biggest cluster is content with requirement of precision, then goto step 4, else $K=K+1$ , goto step 2.
Step 4: If a location within the biggest cluster is fixed by sensors $S_1, S_2, S_3$ and $S_4$ , then the credit of $S_1, S_2, S_3$ and $S_4$ will be added one.
Step 5: Ranking all sensors by their credit, and then pick out outstanding 80% sensors with higher credit value for future computation.
Step 6: Return the center $(a, b, c)$ of the biggest cluster for the future use.

##### Algorithm 1 Voting method

###### 3.1.2 Constraint method

Assuming  $S_1$  and  $S_2$  are two sensors,  $O$  is the microseismic source. According to the theory that the sum length of any two edges of a triangle is not less than the third one, it can be easily known:

$$\begin{cases} D_1 - D_2 \leq S_1 S_2 \\ D_2 - D_1 \leq S_1 S_2 \end{cases} \quad (3)$$

where  $S_1 S_2$  means the distance between two sensors.

If the velocity of the waveform is  $v$ , then we can get the following inequality from Eq. (3) directly.

$$|t_1 - t_2| \leq \frac{S_1 S_2}{v} \quad (4)$$

where  $S_1 S_2$ ,  $t_1$ ,  $t_2$ , and  $v$  are all known. Therefore, we can get  $C(N, 2)$  constraint inequality totally. If the two sensors data did not meet the inequality, they would be removed. The procedure is described in Algorithm 2. In the algorithm, each pair of sensors data will be checked to see if they meet the inequality. If not, they will be deemed as untrustworthy data, and will be removed from the data set. The return value of algorithm is the reliable data set.

Input: Sensor location $(x_i, y_i, z_i)$ , Arrival time $(t_i, i=1, 2, \dots, N_1)$ , Velocity $(v)$ Output: Reliable sensor data set $Q$ . Step 1: $i=1; Q=\{1, \dots, N_1\}$ ; Step 2: $j=i+1$ ; Step 3: if $ t_i-t_j >\sqrt{(x_i-x_j)^2+(y_i-y_j)^2+(z_i-z_j)^2}/v$ , then $Q=Q-\{i, j\}$ ; Step 4: $j=j+1$ ; if $j\leq N_1$ , then goto step 3 Step 5: $i=i+1$ ; if $i\leq N_1$ , then goto step 2 Step 6: Return set $Q$
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**Algorithm 2** Constraint method

If constraint method is executed first, it is probable that data with larger error will make all other data to be discarded. Therefore, in the process of picking data, the voting method should be executed first, and then the constraint method is performed.

### 3.2 Combination of equations

At least four sensors are needed to compute a location in 3-dimentional space. Then we will discuss how the location error will be affected by the distribution of sensors. Assuming four sensors are  $S_0(a_0, b_0, c_0)$ ,  $S_1(a_1, b_1, c_1)$ ,  $S_2(a_2, b_2, c_2)$ ,  $S_3(a_3, b_3, c_3)$ , respectively, then we can list the following equations.

$$D_i = d(a_i, b_i, c_i) = v(t_i - t), i=0, 1, 2, 3 \quad (5)$$

$$\Delta D_i = D_i - D_1 = v(t_i - t_1), i=1, 2, 3 \quad (6)$$

If we differentiate two sides of Eq. (6) at the same time, we can get Eq. (7).

$$\begin{aligned} d\Delta D_i &= v d\tau_{i0} = (C_{i1} - C_{01})dx + (C_{i2} - C_{02})dy + \\ &\quad (C_{i3} - C_{03})dz, i=1, 2, 3 \end{aligned} \quad (7)$$

where

$$\begin{cases} C_{i1} = \frac{\partial D_i}{\partial x} = \frac{x - a_i}{D_i} \\ C_{i2} = \frac{\partial D_i}{\partial y} = \frac{y - b_i}{D_i}, i = 0, 1, 2, 3 \\ C_{i3} = \frac{\partial D_i}{\partial z} = \frac{z - c_i}{D_i} \end{cases} \quad (8)$$

Then we rewrite Eq. (7) to array forms as follows.

$$v d\tau_0 = \mathbf{K} \boldsymbol{\epsilon} \quad (10)$$

where

$$d\tau_0 = [d\tau_{10} \ d\tau_{20} \ d\tau_{30}]^T \quad (11)$$

$$\boldsymbol{\epsilon} = [dx \ dy \ dz]^T \quad (12)$$

$$\mathbf{K} = \begin{bmatrix} C_{11} - C_{01} & C_{12} - C_{02} & C_{13} - C_{03} \\ C_{21} - C_{01} & C_{22} - C_{02} & C_{23} - C_{03} \\ C_{31} - C_{01} & C_{32} - C_{02} & C_{33} - C_{03} \end{bmatrix} \quad (13)$$

Pseudo-inverse method can be used to solve Eq. (10), then

$$\boldsymbol{\epsilon} = v(\mathbf{K}^T \mathbf{K})^{-1} \mathbf{K}^T d\tau_0 \quad (14)$$

From Eq. (14), mean value of the location error can be denoted as follows:

$$E = \sqrt{(dx)^2 + (dy)^2 + (dz)^2} = \sqrt{\boldsymbol{\epsilon}^T \boldsymbol{\epsilon}} \quad (15)$$

Because the above equation is nonlinear, there is no obvious solution. Therefore, simulation is used to get the closest solution. For the sake of obtaining better performance sensors, we divide the layout of four sensors into the following categories and discuss their merits and drawbacks respectively.

**Situation 1:**  $S_0S_1S_2S_3$  in the same plane. Here the arrangement that four sensors located at four corners of a square is simulated, the side length of the square is 10 km,  $d\tau_0 = [0.1 \text{ ms}, 0.1 \text{ ms}, 0.1 \text{ ms}]$ . Figure 3 shows the mesh graph of  $E$  computed according to Eq. (15). By the simulation, it is found that singular area exists in plane  $S_0S_1S_2S_3$ . If the source is in this area, the error will be high. So if sensors distributed like this, they should not be considered to locate the source effectively.

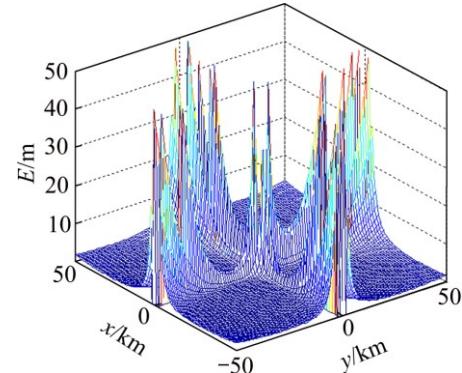


Fig. 3 Error distribution for situation 1

**Situation 2:**  $S_0S_1S_2S_3$  are on the four corners of a tetrahedron respectively, and the projection of  $S_0$  to plane  $S_1S_2S_3$  locates outside of the triangle  $S_1S_2S_3$ . Here, we assign sensors  $S_1$ ,  $S_2$  and  $S_3$  located at three corners of a square with side length of 10 km, and the projection of  $S_0$  to plane  $S_1S_2S_3$  locates to the rest corner.  $d\tau_0 = [0.1 \text{ ms}, 0.1 \text{ ms}, 0.1 \text{ ms}]$ . Figure 4 shows the mesh graph of  $E$  computed according to Eq. (15). By the simulation, it is found that there exists singular area in and out the triangle  $S_1S_2S_3$ . If the source is in this area, the error is colossal. So, it is not a good choice for locating the source accurately if sensors distribute like this.

**Situation 3:**  $S_0S_1S_2S_3$  are on the four corners of a tetrahedron, and the projection of  $S_0$  to plane  $S_1S_2S_3$  locates on the edge of the triangle  $S_1S_2S_3$ . Here, we assign sensors  $S_1$ ,  $S_2$  and  $S_3$  located at three corners of an equilateral triangle with side length 10 km, and the

projection of  $S_0$  to plane  $S_1S_2S_3$  situated on the line of  $S_1S_2$ .  $d\tau_0=[0.1 \text{ ms}, 0.1 \text{ ms}, 0.1 \text{ ms}]$ . Figure 5 shows the mesh graph of  $E$  computed according to Eq. (15). By the simulation, it is found that there exists singular area in and out the triangle  $S_1S_2S_3$ . If the source is in this area, the error is very significant. So, if sensors distribute like this, they should not be considered to locate the source effectively.

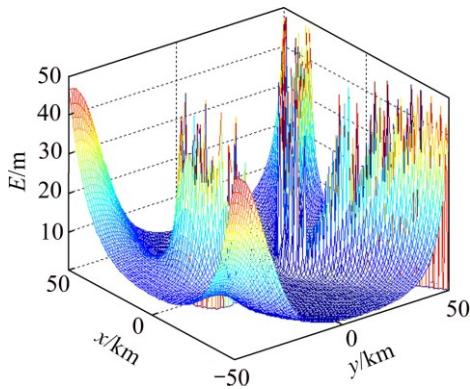


Fig. 4 Error distribution for situation 2

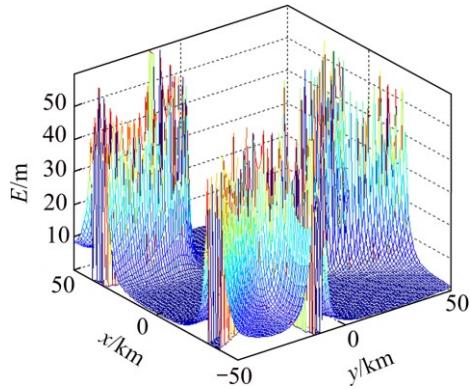


Fig. 5 Error distribution for situation 3

**Situation 4:**  $S_0S_1S_2S_3$  are on the four corners of a tetrahedron, and the projection of  $S_0$  to plane  $S_1S_2S_3$  locates inside of the triangle  $S_1S_2S_3$ . Here, we assign sensors  $S_1$ ,  $S_2$  and  $S_3$  located at three corners of an equilateral triangle with side length of 10 km, and the projection of  $S_0$  to plane  $S_1S_2S_3$  situated in the center of triangle  $S_1S_2S_3$ .  $d\tau_0=[0.1 \text{ ms}, 0.1 \text{ ms}, 0.1 \text{ ms}]$ . Figure 6 shows the mesh graph of  $E$  computed according to Eq. (15). By the simulation, it is found that it is convergent when the source is located on the triangle  $S_1S_2S_3$ . When the source is outside the triangle, the error is also acceptable. Therefore, four sensors distributed like this are the best choice for the precise location.

From the above analysis, it is evident that when the source is located in the tetrahedron  $S_0S_1S_2S_3$ , it has a better performance. Then, we can design the following relocation algorithm.

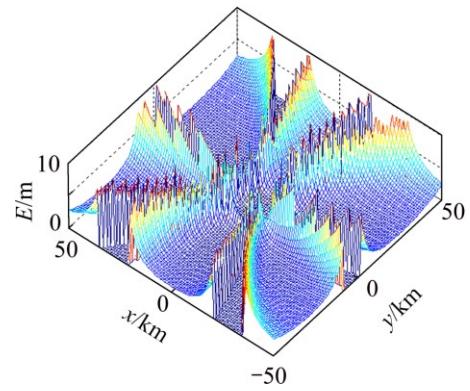


Fig. 6 Error distribution for situation 4

Input: Estimate of source location  $(a', b', c')$ , sensor location  $(x_i, y_i, z_i)$ , TDOA  $(t_{ij})$   
 Output: Source location  $(a, b, c)$   
 Step 1:  $n=1$ ;  
 Step 2: Select 4 sensors arbitrary named  $S_1, S_2, S_3, S_4$ ; if all combination is reached, then go to step 5;  
 Step 3: if  $(a', b', c')$  is in the inside of tetrahedron  $S_1, S_2, S_3, S_4$ , then go to step 4; else go to step 2;  
 Step 4: Use sensors  $S_1, S_2, S_3, S_4$  to locate the source, and the result denoted as  $(a_n, b_n, c_n)$ ;  
 Step 5:  $n=n+1$ ; go to step 2;  
 Step 6:  $a=\text{sum}(a_i)/n, b=\text{sum}(b_i)/n, c=\text{sum}(c_i)/n$ ;  
 Step 7: Return

#### Algorithm 3 Process of relocation method

Here, the  $(a', b', c')$  is gotten from algorithm 1, sensor location and TDOA are known. All sensor groups which include exactly four sensors (named  $S_1, S_2, S_3, S_4$ , respectively) are considered by algorithm 3 in step 2; if  $(a', b', c')$  is located inside the tetrahedron  $S_1S_2S_3S_4$ , then we relocate the position of the source by these sensors and save the result as step 4. When all the sensor quaternaries are considered, the  $k$ -mean method is used to find out a precise centre of those possible locations of the source within all saved results and made it as the return value of the algorithm.

## 4 Experimental

The experiment has been divided into two parts. One is the simulation experiment, and the other is the field experiment. The traditional microseism source location method such as the global optimization method is selected as the reference. For the sake of brevity, we will name them RL(relocation method) and TL(traditional location method) in the ensuing paragraphs respectively.

### 4.1 Simulation

There are some complicated factors like system

errors and noise level that cannot be controlled in real microseism application. Here, synthetized data are used to verify the relocation method. MATLAB is used to simulate a scene, and specify the distribution of the sensor position as shown in Fig. 7. Assume that the  $10\text{ km} \times 5\text{ km} \times 2\text{ km}$  cubic is an ore body, in which 12 s are arranged at the corner and assigned to monitor the vibrated wave. Wave velocity is set as 5.0 km/s. And then 50 microseismic events are generated in space

randomly and sequentially. The arrival time of seismic wave of sensor is calculated by the source location, sensors location and the assumed velocity.

In order to simulate the actual condition as much as possible, white noise is added to smear the simulated seismic wave. Then, these data are used to predict the source location by relocation algorithm and its counterpart. Four configures are assigned as Fig. 8 shows.

The experiment result is shown in Fig. 9, it can be

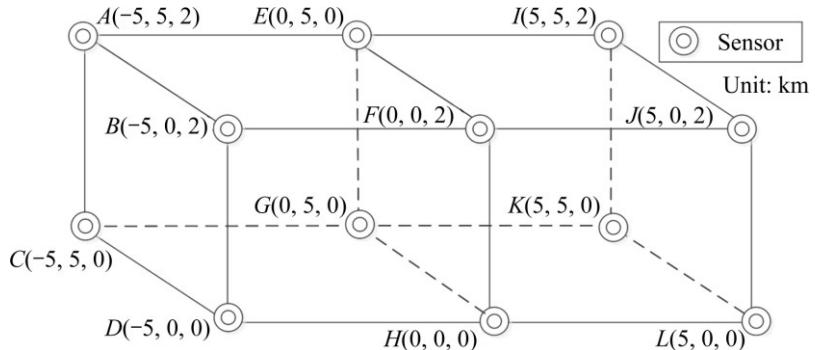


Fig. 7 Distribution of sensors

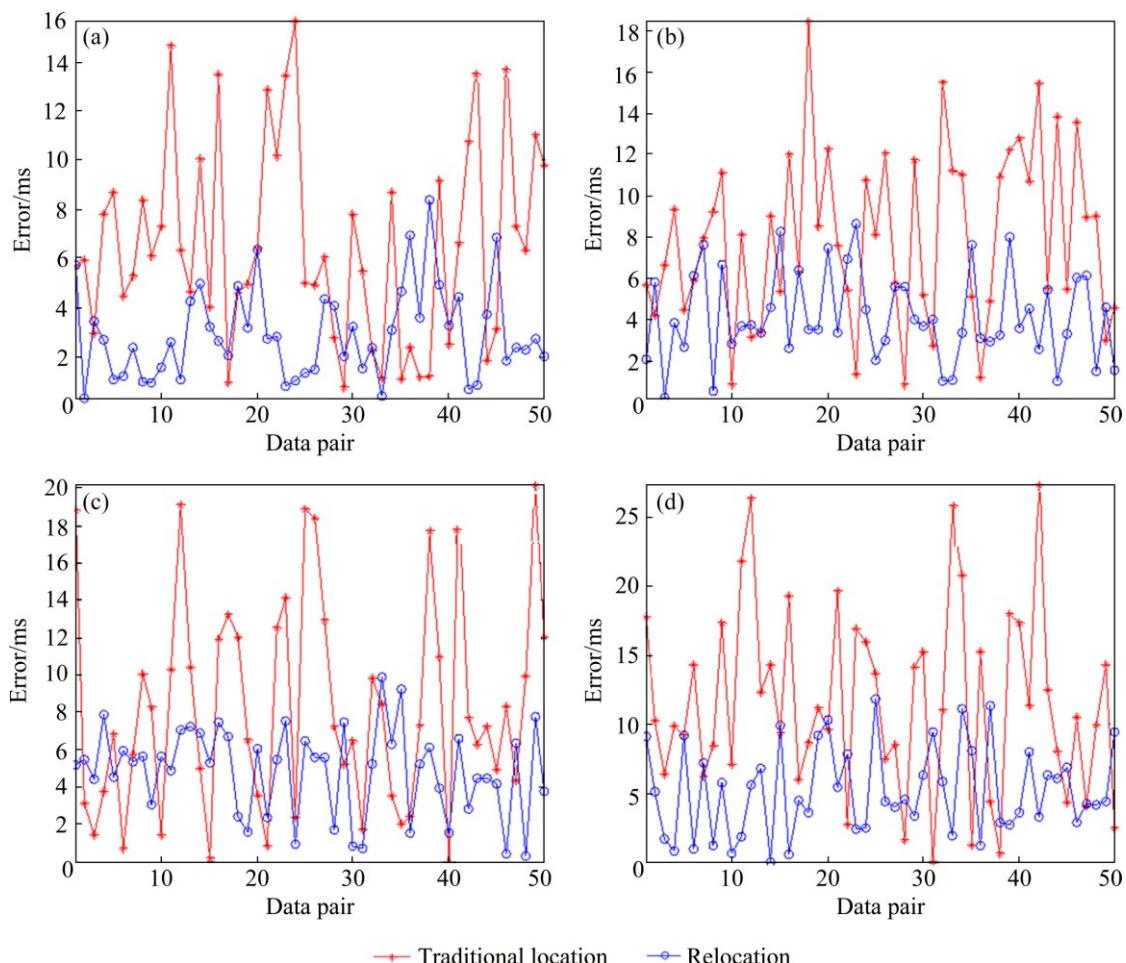
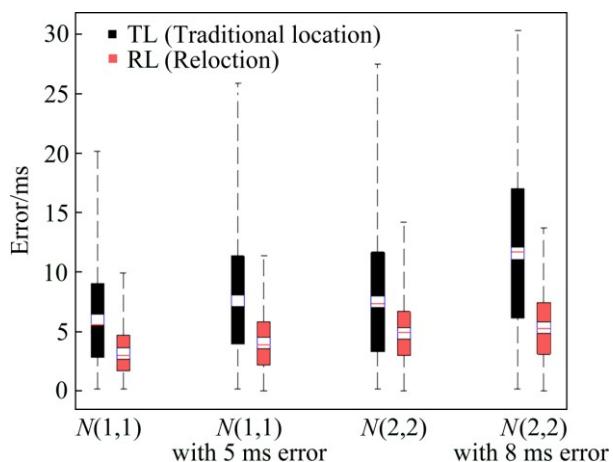


Fig. 8 Location errors when different TDOA are given (here  $N(\alpha, \beta)$  means a normal distribution with mean value  $\alpha$  and standard deviation  $\beta$ ): (a) White noise with 1 ms mean value and 1 ms standard deviation; (b) White noise with 1 ms mean value and 1 ms standard deviation, and a sensor randomly selected with 5 ms error; (c) White noise with 2 ms mean value and 2 ms standard deviation; (d) White noise with 2 ms mean value and 2 ms standard deviation, and a sensor randomly selected with 8 ms error



**Fig. 9** Boxplot of location errors with different methods and TDOA errors

found that when  $N(1 \text{ ms}, 1 \text{ ms})$  normal TDOA errors is introduced, the location error of RL reduced by 36.5% compared with TL. When  $N(2 \text{ ms}, 2 \text{ ms})$  is added to all TDOA, and 8 ms error is added to TDOA of a selected sensor pair, the location error of RL reduced by 39.1% than TL method. The result of other situations are shown in Fig. 9. It is obvious that RL method outperforms TL methods in each situation. It shows that the RL method has a better accuracy in simulation.

#### 4.2 Field experiment

In order to prove the validity of the relocation method in reality, data from microseism monitor system of Dongguashan Copper Mine is chosen to verify the precision of the RL algorithm. The monitor system is called integrated seismic system (ISS), which is developed by South Africa ISS International Corporation. 18 single component sensors are arranged in three tunnels to monitoring microseismic events for 24 h for 365 d. Then, 3 blasting events with the known location are executed. The location coordinate of blast is shown in Table 1.

We take each blast as a microseismic event and predict the location of blasts by the arriving time recorded by sensors. There are 18 sensors deployed in the mine totally. The location of sensors is shown in Table 2.

Similar with the simulation part, the relocation method is compared with the traditional microseism source location method in field experiment. For each

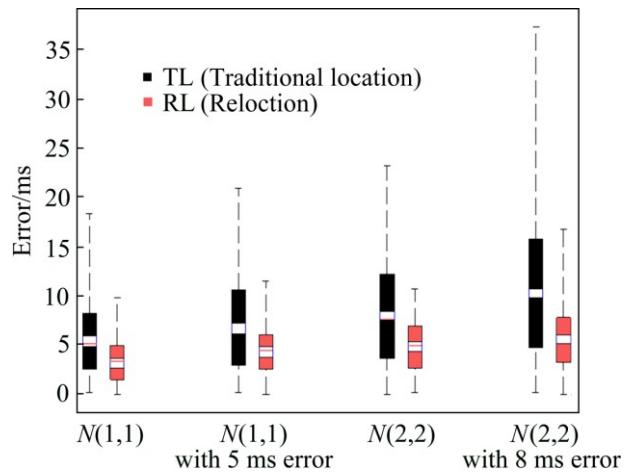
**Table 1** Location of blast experiment

Blast ID	X	Y	Z
1	84528	22556	-753
2	84479	22570	-814
3	84359	22673	-795

**Table 2** Location of sensors

Sensor ID	X	Y	Z	Sensor ID	X	Y	Z
1	84345	22474	-678	9	84591	22453	-862
2	84157	22717	-737	10	84349	22271	-862
3	84256	22587	-682	11	84429	22332	-863
4	84493	22395	-653	12	84509	22391	-862
5	84299	22861	-764	13	84076	22705	-862
6	84377	22755	-722	14	84182	22775	-862
7	84487	22612	-704	15	84259	22840	-862
8	84580	22489	-693	16	84307	22943	-860

blasting event, the computation is executed 50 times with random TDOA error. And four noise levels are considered. The results are compared in Fig. 10. When  $N(1 \text{ ms}, 1 \text{ ms})$  normal TDOA errors exist, the location error by RL method is reduced by 42.5% than TL method. When  $N(2 \text{ ms}, 2 \text{ ms})$  normal TDOA errors and 8 ms assumed sensor error exist, the location error of RL method is reduced by 41.8% compared with TL method. The results of other situations are shown in Fig. 10. In general, the RL outperforms TL method and gives more accurate locating results in the field computation.



**Fig. 10** Boxplot of location errors in field experiment

#### 5 Conclusions

1) The location precision of micro-seismic source can be improved in following ways when there are abundant sensors data available: I) Removing incredible data by the constraint of the model; II) Removing the inappropriate equations that may amplify the sensor error; III) Voting for locations by different sensor groups by  $k$ -mean cluster.

2) The location error of relocation method is

reduced by 41.8% compared with traditional location method when error of normal distribution with mean value 2 ms is added.

3) The relocation method can improve the fault-tolerant performance significantly and get more accurate location results. It will play an important role in later practical application. In future, we will explore the use of machine learning in removing both incredible data and inappropriate equations.

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# 一种深部矿井中微震源的二次定位方法

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**摘要:** 本文作者提出了一种新的二次定位的方法, 这是首次系统地利用大量的传感器信息来降低传感器误差和噪声对定位造成的影响, 它是通过多组数据之间交叉检验来提高定位的精度。方法的过程是: 首先根据传感器位置等因素给出每个传感器监测到的数据的可靠度, 使用可靠度较高的数据进行震源位置的初步测算, 然后根据初始定位的结果和传感器位置的相对关系选择具有最优噪音容忍度的一组方程, 并通过 *k*-mean 投票法确定最终的震源位置。对传统定位方法和本文提出方法进行了比较以验证方法的可靠性, 并分别使用模拟和现场试验数据进行了定位测算。在现场试验中, 当 TDOA 加入了  $N(2,2)$  的正态分布误差, 与传统方法相比, 本文方法的定位误差降低了 41.8%。实验结果表明本文提出的二次定位法能够显著提高容错性能, 得到更为精确的定位结果。

**关键词:** 微震; 二次定位; *k*-mean; 方程选择; 传感器布置

(Edited by Yun-bin HE)