

# Accurate Localisation of Multiple Rocket Debris Based on Genetic Algorithms

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## abstract

This paper proposes an accurate positioning method for rocket debris based on genetic algorithm. The rocket debris will produce supersonic sonic boom in the process of falling, this paper realises the high precision positioning of the sonic boom position and time of the rocket debris by arranging multiple vibration wave monitoring devices in the debris theoretical fallout area, constructing a set of multilateral measurement equations by using the difference in the arrival time of the sonic boom, and introducing genetic algorithms to optimally solve the hyperbolic equations to achieve high precision positioning of the sonic boom position and time of the rocket debris. The results show that the genetic algorithm can effectively avoid the local optimum problem of the traditional method and significantly improve the positioning accuracy. In addition, this paper also explores the error analysis model and the optimisation method of monitoring equipment arrangement, which further improves the reliability and adaptability of the positioning system.

**Keywords:** Rocket Debris Recovery, Genetic Algorithm, Sonic Boom Positioning, MLM, Optimisation Algorithm

## 1 | Introduction

In the history of mankind, space exploration has always been a key force in promoting scientific and technological progress and expanding the boundaries of human existence. From early satellite launches to deep space exploration missions, the success of each step cannot be separated from the rocket technology behind [1]. Due to the high cost and complexity of the rocket launching process, the recycling and reuse of rocket debris has become increasingly important. Currently, the vast majority of rockets use a multi-stage rocket structure, in which the following stage or booster is separated and crashed to the ground by inter-stage separation after completing the set mission [2]. During the fall, due to the rapid passage of the atmosphere, the debris exceeds the speed of sound generating a super-helical sonic boom. A sonic boom is a

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strong vibrational fluctuation caused by acoustic compression when debris moves faster than the speed of sound advancing.

These rocket parts falling to the ground have potential reuse value, and at the same time pose a threat to the facilities and safety on the ground. Therefore, the accurate recovery and reuse of rocket debris becomes especially important [3]. In order to quickly recover the rocket debris can be arranged in the debris theoretical fallout area of multiple vibration wave monitoring equipment, in order to receive different rocket debris from the air from the transonic sonic boom, and then according to the arrival time of the sonic boom, the location of the airborne debris when the sonic boom occurs, and then finally using ballistic extrapolation to achieve rapid and accurate positioning of the debris landing point [4].

## 2| Literature Review

In the past research of scholars, the time-difference localisation method and area localisation method are the main methods of acoustic emission source localisation. The basic method of time-difference localisation is to solve the equation by taking the propagation speed of the acoustic emission signal, the positional coordinates of the sensors and the time difference between the arrival of the signal at the sensors as known quantities, and the coordinates of the acoustic emission source as unknown quantities. According to the type of positioning object is divided into one-dimensional linear positioning, two-dimensional planar positioning and three-dimensional body positioning. For  $n$  ( $n=1, 2, 3$ ) dimensional time difference localisation, at least  $n+1$  sensors are required. The accuracy of time difference positioning depends on the measurement accuracy of the arrival time difference and propagation speed, in practice, the acoustic emission signal is subject to the anisotropy of the medium and its scattering and attenuation in the propagation process and it is more difficult to get the accurate propagation speed, generally using the average propagation speed instead of the average propagation speed, with a limited range of applications and positioning accuracy [5]. The basic method of regional positioning method is: according to the shape of the device under test and the detection range of the sensor, the area to be tested is divided into a number of small areas, placed in each small area of the sensor, by comparing the intensity of the signal received by each sensor to determine the approximate region of the acoustic emission source. Area positioning method positioning method is fast, simple, rough, suitable for simple structure, uniform material objects [6].

Ziola et al. used the mutual correlation function method to calculate the signal arrival time difference, and the experiments showed that the method was effective in locating the aluminium plate [7]. Y. Ding et al. used the wavelet decomposition method to obtain the arrival moment of the signal, and solved the problem that the arrival moment was difficult to be determined due to the inhomogeneity of the propagation medium [4]. Kundu used the mathematical extremum problem to obtain the position of the acoustic emission source, and studied the problem of

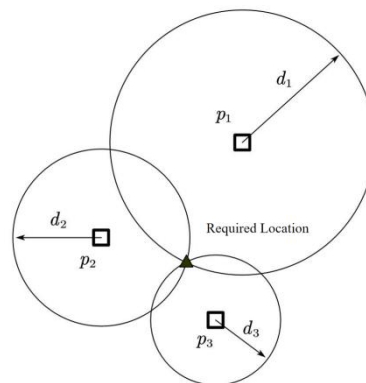
locating the source in fibre-reinforced composite plates [8]. Holford et al. used the method of acoustic emission source location in fibre-reinforced composite plates to locate the damage position of bridges by means of acoustic phase velocity and intensity for the condition monitoring of bridge structures [9,10]. Nivesrangsan et al. used two-dimensional planar localization method to locate the faults of an engine, and arranged the sensors in triangular arrays to compare the arrival time difference of the received signals and the signal strengths of the sensors [11]. The arrival time difference and signal-to-noise ratio of the received signals are compared to identify the fault location, and the algorithm achieves a better recognition effect [11].

### 3| Methodology

#### 3.1 Individual Rocket Debris Localisation based on Polygonal Measurements

The latitude, longitude, elevation and sonic boom arrival time data provided by the monitoring equipment allow us to determine the positional coordinates and time of the sonic boom when it occurs for individual rocket debris in the air. Through the mathematical relationship between the position and time of sonic boom occurrence, a system of equations is constructed to solve for the unknown parameters, and the minimum number of monitoring devices required is deduced based on the number of equations. In order to improve the positioning accuracy, this paper transforms the seven sets of redundant data into an optimisation problem, sets the minimisation of positioning error as the objective function, and the position and time of the tone burst as the decision variables, so as to establish an optimisation model. Ultimately, this optimisation model is solved using genetic algorithm to ensure more accurate positioning results.

In order to determine the airborne sonic boom position and sonic boom moment of a single wreckage, we can build a system of non-linear equations based on distances according to polygonal measurements.



**Fig. 1 Principle of In-plane Polygonal Measurement Method**

Let the location of the sonic boom be  $(x, y, z)$ , and its sonic boom time be  $t$ , then the following equations can be listed:

$$(x - x_i)^2 + (y - y_i)^2 + (z - z_i)^2 = d_i^2$$

Where  $(x_i, y_i, z_i)$  for the location of the monitoring equipment coordinates,  $d_i$  for the sonic boom to the detection equipment  $i$  distance. Considering that in practice, the monitoring device monitoring time zero and sonic boom moment does not necessarily match, the distance calculated will have a certain degree of error, so we might as well set the first  $i$  monitoring device measured sonic boom vibration wave arrival time for  $t_i$ , sonic boom vibration wave arrival time to monitor the actual time of the monitoring device for  $t$ ,  $v$  is the speed of sound, then can be listed:

$$d_i = v(t_i - t)$$

Joining the above equations gives

$$(x - x_i)^2 + (y - y_i)^2 + (z - z_i)^2 = [v(t_i - t)]^2$$

represents the relationship between the data from the  $i$ th monitoring device and the location and time of the sonic boom. The equation contains 4 unknowns  $(x, y, z, t)$ , and at least four different sets of equations are needed to find a unique solution. Therefore, data from at least 4 monitoring devices are required. When there are more than 4 monitoring devices, the system of equations is a super-definite system of equations.

We may as well convert latitude, longitude and elevation into a right-angle 3D coordinate system, i.e. Cartesian coordinate system. Let the latitude, longitude and elevation of the  $i$ th device be  $(a_i, b_i, c_i)$ , which is converted by the following equation:

$$(x_i, y_i, z_i) = \begin{cases} x_i = 97.304 * 1000 * (a_i - a_0) \\ y_i = 111.263 * 1000 * (b_i - b_0) \\ z_i = h_i \end{cases}$$

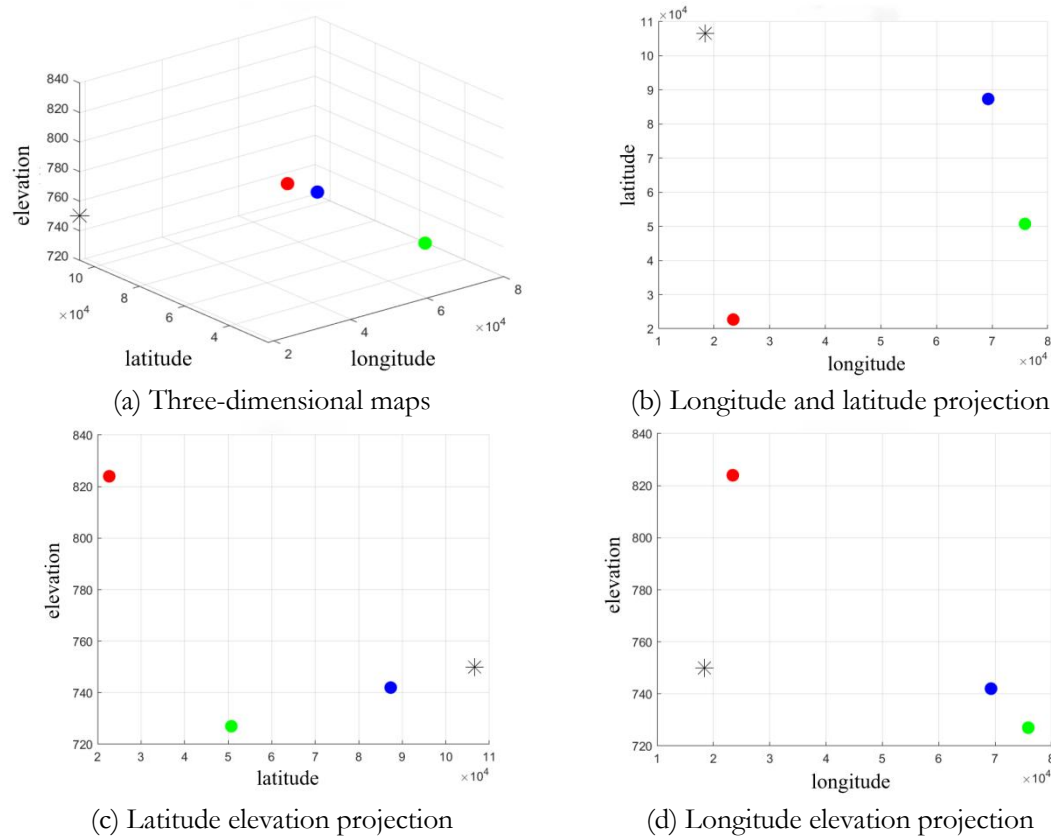
Where  $(a_0, b_0)$  is the latitude and longitude of the coordinate origin, and the unit of  $(x_i, y_i, z_i)$  in the above transformation formula is metre. Let us set point G as the origin of the coordinates, then we can derive the following table 1:

**Table 1 Cartesian Coordinates of each Device and Arrival Time of the Sonic Boom**

| appliances | x-coordinate/km | y-coordinate/km | z-coordinate/m | Sonic boom arrival time/s |
|------------|-----------------|-----------------|----------------|---------------------------|
| A          | 18.884          | 9.235           | 824            | 100.767                   |
| B          | 71.350          | 37.273          | 727            | 112.220                   |
| C          | 64.731          | 73.879          | 742            | 188.020                   |
| D          | 19.857          | 78.329          | 850            | 258.985                   |
| E          | 46.431          | 55.186          | 786            | 118.443                   |
| F          | 40.883          | 89.010          | 678            | 266.871                   |
| G          | 0               | 0               | 575            | 163.024                   |

We randomly used the coordinate positions and sonic boom arrival times in Table 1, as well as the latitude, longitude, and altitude of each detection device, to create spatial equations, each corresponding to a detection device.

Finally, we need to find the latitude, longitude, elevation and time of the sound outbreak, a total of four unknown quantities. When solving the problem, we can first solve the three joint equations to obtain the three unknown quantities, and then bring in a non-repeating set of data to calculate the last unknown quantity  $t$ . This step-by-step approach can simplify the calculation process and reduce the amount of computation. In order to further verify the accuracy of the results and reduce the error, we will solve all seven sets of data, and if the selected equipment is larger than four, the problem becomes the solution of the super-definite equation, which is transformed into a least-squares problem first, and then solved, which can further improve the precision and accuracy. The solution results and their visualisation images are shown in Figure 1.



**Fig. 2 Predicted position of the sonic boom and the position of the detection device in Cartesian coordinates**

From the calculation, the latitude and longitude of the sonic boom is  $(111.1962^\circ, 26.6370^\circ)$ , and the elevation is 748.3422 m. Then bring in any one of the non-repeatable monitoring equipment data to find the time of the sonic boom  $t = 0.025204s$ .

Because the number of monitoring devices is greater than 4, the equation is a hyper-definite

system of equations, in order to make full use of the data, we can use the data to build an optimisation model to find its optimal solution. The objective function is constructed by minimising the sum of the residuals of the sonic boom arrival time and the actual arrival time measured by all the monitoring devices as follows:

$$\min \sum_{i=1} \sqrt{(x - x_i)^2 + (y - y_i)^2 + (z - z_i)^2} - [v(t_i - t)]$$

where based on the data in the table and rough extrapolation, we can set the constraint as

$$\text{s.t. } \begin{cases} x \in [-10^5, 10^5], & y \in [-10^5, 10^5] \\ z \in [0, 10^4], & t \in [-100, 200] \end{cases}$$

Thus, by solving this least squares problem, we can calculate the optimal solution for the location and moment of the sonic boom of the wreckage with the data from the seven monitoring devices. To solve the least squares problem, we use a genetic algorithm.

### 3.2 Genetic Algorithm to Solve the Overdetermined Multi-Point Localisation Problem

Genetic algorithm is a heuristic algorithm based on biological genetic mechanism, as a heuristic search algorithm, it is very suitable for solving complex and non-linear optimisation problems such as super fixed multipoint localisation.

It is first assumed that the search space represents all possible sonic boom locations, and that each individual represents a potential sonic boom in the genetic algorithm. The position coordinates of the wreckage sonic boom  $(x, y, z)$  and the sonic boom  $t$  are encoded as a four-dimensional vector, which is set as the individual of the genetic algorithm. To facilitate subsequent calculations, the four components will be normalised to map their range into the interval  $[0, 1]$ , denoted as  $.s = (s_x, s_y, s_z, s_t)$

Randomly generate an initial population of  $N$  individuals  $S^{(0)} = \{s_1^{(0)}, s_1^{(0)}, \dots, s_n^{(0)}\}$ ,  $N$  is the population size. Construct a fitness function to evaluate the degree of superiority or inferiority of each individual in the population, which we denote by the localisation error correlation:

$$G(s) = \frac{1}{\sum_{i=1}^n f_i^2(s) + c}$$

Here we introduce a smoothing parameter  $c$ , which provides a non-zero minimum value for the denominator to ensure numerical stability. Where  $f_i(s)$  is the positioning error of the  $i$ th station,

i.e:

$$f_i(s) = \sqrt{(x - x_i)^2 + (y - y_i)^2 + (z - z_i)^2} - v(t_i - t)$$

The larger the fitness value, the smaller the deviation between the individual's predicted position and the true position, i.e., the smaller the individual's localisation error, and the more superior the individual is.

The selection strategy determines which individuals are able to participate in the subsequent crossover and mutation operations, and the probability of each individual being scored is proportional to its fitness value, i.e:

$$p_i = \frac{G(s_i)}{\sum_{j=1}^N G(s_j)}, i = 1, 2, \dots, N$$

The new populations selected are randomly paired two by two, while a crossover operation is performed with a certain crossover probability  $P_c$  to generate new individuals, yielding the following relational equation:

$$\begin{cases} s_i = (s_{i1}, s_{i2}, \dots, s_{i4}) \\ s_j = (s_{j1}, s_{j2}, \dots, s_{j4}) \end{cases} \rightarrow \begin{cases} s_i' = (s_{i1}, \dots, s_{k4}, s_{j,k+1}, \dots, s_{j4}) \\ s_j' = (s_{j1}, \dots, s_{j4}, s_{i,k+1}, \dots, s_{i4}) \end{cases}$$

Using a certain probability of variation  $p_m$ , small perturbations were applied to each component of each individual:

$$s_{ij}' = \begin{cases} s_{ij} + r * \delta & \text{if } r < p_m \\ s_{ij} & \text{otherwise} \end{cases}$$

Where  $r$  is the random number in the range, which is used to control the size of the perturbation, and  $\delta$  is the mutation step, which determines the magnitude of the random number  $r$  after scaling, and thus controls the strength of the mutation.

When the result reaches the maximum number of evolutionary generations, or stops running when the change in fitness value is less than a threshold, we can consider the individual with the highest fitness value in the final population as the global optimal solution. The optimal solution can be obtained by implementing the above algorithm using MATLAB's Genetic Algorithm Toolbox.

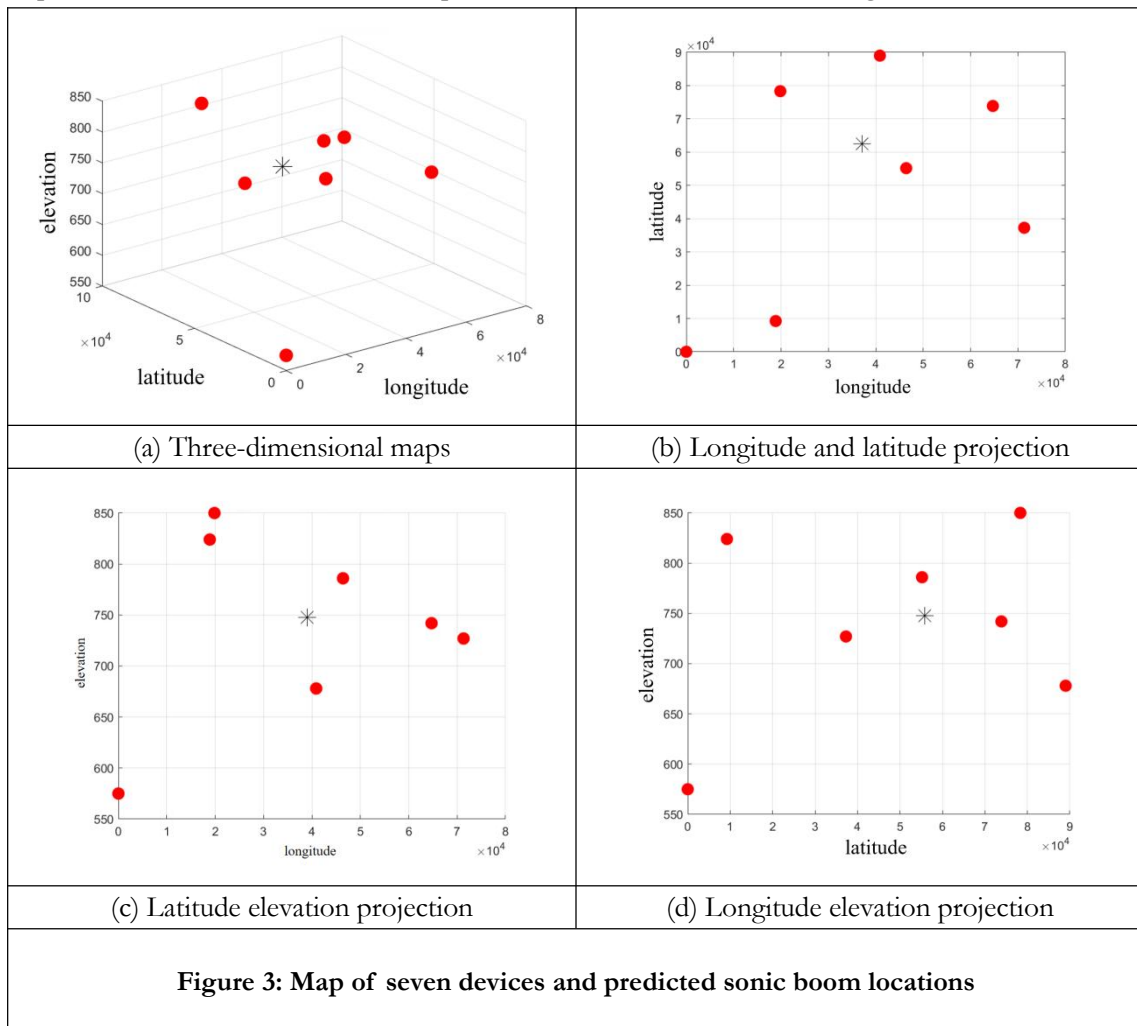
We can set an initial value as the average of all observation points, set the range of the sonic boom point, the latitude range is  $[27^\circ, 29^\circ]$ , the altitude range is  $[1, 10]$ , and the time range is  $[0, 200]$  seconds. The population size is taken as  $N=100$ , variation probability

$p_m = 0.1$ , variation step = 0.05, crossover probability  $p_c = 0.8$ , and the maximum number of evolutionary generations is 600. The above algorithm is implemented by using the ga function of the Genetic Algorithm Toolbox in the Optimisation Toolbox of MATLAB, and the optimal individual is obtained as follows: coordinates  $s=(110.9471^\circ, 26.8800^\circ, 748.7830\text{m})$ ,  $t=0.108782\text{s}$ .

The longitude of the sonic boom is  $110.9471^\circ$ , the latitude is  $26.8800^\circ$ , the altitude is 748.7830m, and the moment of the sonic boom is the first 0.108782s, and the results are to be used in 7 stations, and the root mean square error is 0.344s, which is a good positioning accuracy.

### 3.3 Genetic algorithm solution results

In the case of increasing to seven monitoring devices, the positioning accuracy can be further improved by constructing a system of super-determined nonlinear equations. The commonly used methods for solving such least squares problems include weighted least squares, regularisation and robust estimation. Here we use genetic algorithm instead of traditional methods, although its convergence speed is relatively slow, as a global optimisation algorithm, it can find the optimal solution in a wider search space, and it is not easy to fall into the local optimum, and the results of the computation are visualised as shown in Fig. 3.



### 3.4 Error analysis models

In large-scale IoT, due to the influence of hardware errors, network attacks, insufficient energy, bad weather and other practical environmental factors, the collected data often contain large errors, thus affecting the positioning results, especially in the time when the vibration wave is received by the monitoring device. We can introduce it into the equation established in the previous problem II to describe the actual situation more accurately. Let the time when the  $i$ th device receives the arrival of the vibration wave from the  $j$ th wreckage be  $\tilde{T}_{ij}$ , and let the error between him and the actual arrival time  $T_{ij}$  be  $\delta_{ij}$  that is

$$\tilde{T}_{ij} = T_{ij} + \delta_{ij}, \quad i = 1, 2, \dots, n; j = 1, 2, \dots, m$$

Where  $n$  is the number of monitoring equipment,  $m$  is the number of debris in the air, and from the question  $\delta_{ij}$  obeys the uniform distribution on the interval  $[-0.5, +0.5]$ , i.e.  $\delta_{ij} \sim U(-0.5, +0.5)$ , then the equation with the error factor can be varied as:

$$\sqrt{(x_j - x_i)^2 + (y_j - y_i)^2 + (z_j - z_i)^2} = v(\tilde{T}_{ij} - t_j)$$

In order to reduce the impact of time errors  $\delta_{ij}$  on the accuracy of the positioning results, separate processing optimisation of both the positioning algorithm and the placement of the monitoring device can be used.

#### 3.4.1 Iterative reweighted least squares method

The conventional least squares method gives the same weight to all measurements when processing them, which may introduce large errors in practical applications. The weighted least squares method assigns different weights to different measurements by introducing an error-dependent weighting factor. That is, large weights are assigned to points with small absolute errors, while small weights are assigned to points with large absolute errors. The above model is modified to update the objective function:

$$\min_{x_i, y_i, z_i, t_i} \sum_{i=1}^m \sum_{j=1}^n \mu_{ij} \left( \sqrt{(x_i - X_j)^2 + (y_i - Y_j)^2 + (z_i - Z_j)^2} - v(T_{ij} - t_i) \right)^2$$

Where  $\mu$  is the weighting factor of the  $i$ th monitoring device for the  $j$ th debris measurement, which is set here as the reciprocal of the measurement residual.

$$\mu_{ij} = \frac{1}{\left| \sqrt{(x_i - X_j)^2 + (y_i - Y_j)^2 + (z_i - Z_j)^2} - v(T_{ij} - t_i) \right| + c}$$

Where  $c$  is a very small positive number to avoid the denominator of the equation being zero.

#### 3.4.2 Optimisation of monitoring equipment layout

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The accuracy of a positioning system is affected not only by the robustness of the algorithms used, but also by the number of monitoring devices and their spatial layout. Theoretically, increasing the number of monitoring devices enhances the redundancy and coverage of the data, thereby improving the accuracy of the positioning results. This is because more data points mean a richer set of information that can be used to more accurately determine the location of a target. However, in practice, increasing the number of devices also means increased system complexity and maintenance costs, requiring more infrastructure support, data processing power and storage space. Therefore, a combination of accuracy requirements and practical resource constraints must be considered when determining the number of monitoring devices.

#### (1) Maximal Mutual Information (MMI)

The MMI criterion is a tool used in information theory to quantify the degree of association between two random variables. In Problem 4, we assume that the location of the monitoring equipment on the ground is described by the random variable  $X$ , while the spatial location of the airborne debris and the moment of the sonic boom are described by the random variable  $Y$ . Then the mutual information  $I(X, Y)$  of  $X, Y$  can be expressed as

$$I(X; Y) = H(Y) - H(Y|X)$$

Where  $H(Y)$  represents the entropy of the random variable  $Y$ , which represents the uncertainty of the random variable  $Y$ , the larger the entropy, the larger the uncertainty, and  $H(Y|X)$  represents the uncertainty of the random variable  $Y$  under the condition of the known random variable  $X$ , it can be known that the larger the mutual information is, the smaller the uncertainty between the random variable  $X$  (the position of the monitoring equipment) and the random variable  $Y$  (the spatial position of the airborne debris and the moment of the sonic boom), and the greater the accuracy of its positioning. Therefore, we can optimise the position of the detection equipment by maximising the value of mutual information, thus setting the objective function as

$$\max_{X_i Y_i Z_i} I(X; Y), \quad (X_i, Y_i, Z_i) \in \mathcal{F}, \quad i = 1, 2, \dots, n$$

Where  $\mathcal{F}$  indicates the feasible installation area of the monitoring equipment, which can be placed according to the local terrain, safety distance and other factors

#### (2) Geometric Dilution of Precision (GDOP) guidelines

For the optimisation of the positional arrangement of the inspection equipment, we introduce a minimum geometric accuracy factor criterion. The GDOP is often used in spaceflight to measure the influence of the spatial geometric distribution of satellites on their positioning accuracy. We substitute the latitude, longitude and elevation of the monitoring equipment for the GDOP, and

the smaller the value of GDOP, the more uniform the geometric distribution of the monitoring equipment is, the smaller the influence on the positioning accuracy, and the higher the positioning accuracy. Where GDOP is defined as follows.

$$GDOP = \sqrt{\text{tr}((H^TH)^{-1})}$$

where H is the design matrix whose elements are:

$$h_{ij} = \frac{x_j - x_i}{d_{ij}}, h_{ij+m} = \frac{y_j - y_i}{d_{ij}}, h_{ij+2m} = \frac{z_j - z_i}{d_{ij}}, h_{ij+3m} = -v$$

### 3.4.3 Optimisation validation

In order to verify the effectiveness of the above positioning algorithm as well as the monitoring device placement algorithm, we have eight randomly generated monitoring devices, given their latitude and longitude coordinates and four measured sonic boom arrival times, and four rocket debris with known location coordinates and sonic boom times . We quantitatively assess the accuracy of the algorithm by means of the root mean square logarithmic error (RMSE) metric.

**Table 2 Prediction of Hypothetical Wreckage Locations by Two Algorithms**

| Positioning Algorithm | Wreckage 1 RMSLE (m) | Wreckage 2 RMSLE (m) | Wreckage 3 RMSLE (m) | Wreckage 4 RMSLE (m) | Average RMSLE (m) |
|-----------------------|----------------------|----------------------|----------------------|----------------------|-------------------|
| General LS            | 425.6                | 517.3                | 389.2                | 450.8                | 450.1             |
| IRLS                  | 316.4                | 394.5                | 285.7                | 337.9                | 337.4             |

**Table 3 RANSAC Algorithm to Get the Wreckage Location and Explosion Moment**

| Layout Optimisation Guidelines | Wreckage 1 RMSE (m) | Wreckage 2 RMSE (m) | Wreckage 3 RMSL (m) | Wreckage 4 RMSE (m) | Average RMSE (m) |
|--------------------------------|---------------------|---------------------|---------------------|---------------------|------------------|
| Initial Deployment             | 258.9               | 326.5               | 237.7               | 295.7               | 279.9            |
| G DOP Optimisation             | 203.4               | 264.4               | 192.3               | 231.4               | 223.1            |
| MMI Optimisation               | 189.8               | 253.7               | 178.7               | 219.8               | 210.3            |

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It can be seen that after the optimised deployment, the positioning errors of the wreckage are reduced by 20.33% and 24.89% respectively. The optimisation scheme based on the MMI criterion is slightly better than the GDOP criterion in terms of error reduction, and through the reasonable deployment of monitoring equipment, it can effectively reduce the impact of measurement error on the positioning performance, and further improve the accuracy and reliability of the positioning system.

## 4| Conclusion

This paper investigates the accurate positioning method of multiple rocket debris based on genetic algorithm. Through the introduction of multilateral measurement method and genetic algorithm optimisation solution, the problem of high-precision positioning of the sonic boom position and time of the rocket debris is successfully solved. The results show that the genetic algorithm can effectively deal with the super-definite nonlinear equations, avoiding the problem of traditional methods falling into the local optimum, and significantly improving the positioning accuracy. However, the convergence speed of the genetic algorithm is slow, which is difficult to meet the real-time requirements. At the same time, the positioning accuracy is highly dependent on the quality and quantity of data from the monitoring devices, and the results are greatly affected by sensor failures and environmental noise in practical applications.

Future research direction can explore the combination of genetic algorithm and other optimisation algorithms to improve the convergence speed of the algorithm; meanwhile, we can further optimise the arrangement of the monitoring equipment to improve the robustness of the system against noise and missing data. We can also improve the sonic boom propagation model by combining it with the actual atmospheric environment model, so as to better adapt to the localisation requirements in complex environments.

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