Separation Algorithm of Fixed Wing UAV Positioning Signal Based on AI

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Abstract. Unmanned aerial vehicle (UAV) is an unmanned aircraft remotely controlled by radio, which is widely used in reconnaissance. However, during the operation of UAV, the positioning signal is easily disturbed by noise, which leads to low separation accuracy and poor positioning effect of fixed wing UAV. To this end, a fixed wing UAV positioning signal separation algorithm based on artificial intelligence is proposed. The fixed-wing UAV positioning signal denoising algorithm is constructed by collecting the feature information of fixed-wing UAV, and the denoising of fixed-wing UAV positioning signal is completed. In order to reduce the signal separation error and realize the fixed wing UAV positioning signal separation, signal separation is processed according to the positioning signal algorithm. Experimental results show that the proposed algorithm can effectively separate the UAV location signal from the noise, and has high accuracy and good location effect under serious multipath interference.

Keywords: Artificial intelligence · Fixed-wing UAV · Positioning signal · Signal separation

1 Introduction

UAV has been widely used in many fields such as national defense, agriculture and military because of its flexibility, maneuverability and small size. Signal recognition and separation of UAVs play an important role in their stability and safety. When the UAV is located passively, the multipath noise caused by obstacles on the ground is uncertain and irrelevant in different positions, so it is impossible to locate the UAV in real time. Therefore, it is of great significance to study the separation technology of UAV positioning signals.

Reference [1] proposes the research of UAV positioning signal separation algorithm based on support vector machine, which obtains information entropy by calculating the Euclidean distance between adjacent data sets of UAVs, and provides model data for SVM to map high-dimensional space. On this basis, the threshold soft boundary of the mapping function is added to make the model have the ability of parameter adaptive adjustment to adapt to the data difference caused by the flexible movement of

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UAV. Finally, the observer operating characteristic curve is constructed to obtain the separation results of UAV positioning signals. This algorithm can effectively separate the UAV positioning signal and noise, but when the signal-to-noise ratio is small, the positioning performance of the algorithm is poor.

According to the characteristics of fixed wing UAV, the signal is collected. Through the features of the fixed wing UAV, the positioning feature signals are collected. The momentum term is combined with the adaptive algorithm to improve the signal denoising effect. After the UAV positioning points are arranged, the positioning data is obtained. According to the similarity between the execution trajectories, the fixed wing UAV positioning signal is separated, which improves the accuracy of UAV positioning.

2 Positioning Signal Separation Algorithm for Fixed-Wing UAV

2.1 Characteristics of Fixed Wing UAV

Fixed-wing UAV is widely used in remote sensing and aerial survey because of its convenience and flexibility. Fixed-wing UAV can be used in remote sensing and aerial survey. Fixed-wing UAV remote sensing is composed of three parts, namely, control, fixed-wing UAV remote sensing platform and image processing. Its main functions include: using control to complete the route planning and flight route control of the fixed-wing UAV, the route planning can set flight routes and specify flight tasks, and the flight route control can be used for real-time flight control and interactive operation; using the fixed-wing UAV remote sensing platform to carry the transmission of data by sensors, which is mainly composed of four-wing UAV, camera, pan tilt and GPS positioning, can complete direct photography to the ground, and its flight position data can be transmitted in real time; image processing mainly carries out image processing, including image rectification, fusion and mosaicing, and on this basis, can be expanded, for example, direct query and browsing of images.

2.2 Fixed Wing UAV Positioning Signal Acquisition

The process for collecting the positioning signal of the fixed-wing UAV is shown in Fig. 1.

As can be seen from Fig. 1, before each operation, the fixed-wing UAV needs to locate the probing area, determine the route, and then inject the route into the remote sensing flight platform; with the assistance of GPS positioning, shoot according to the planned route, and obtain the image sequence; if the aerial photography is completed, the acquired image information shall be transmitted to the processing center, and a series of image processing such as rectification, fusion and mosaic shall be completed, and the image shall be stored so as to further deal with the feature processing of the large impact. The fixed wing UAV needs to operate with zero error in all the above steps. To do this, a fixed wing UAV positioning coordinate system must be established first, and then the target can be located [2]. In the process of UAV positioning, the entropy data of UAV positioning information is extracted as the core function of positioning signal to map dimensions. The more uniform the probability of the random distribution of the

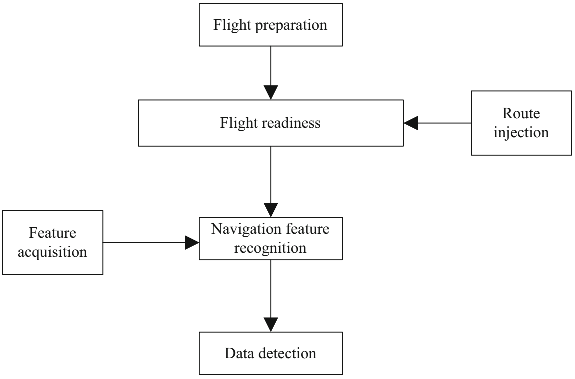

Fig. 1. Feature acquisition of fixed wing UAV positioning signal

UAV positioning signal, the greater the entropy, and vice versa. Therefore, the UAV positioning signal is obviously different from the normalized information entropy data and multipath noise data.

Artificial intelligence refers to the technology of presenting human intelligence through ordinary computer programs, for mapping high dimensional space by calculating the Euclidean distance between adjacent UAV datasets. On this basis, the soft boundary of mapping function is added to make the model have the ability of parameter adaptive adjustment to adapt the data difference caused by UAV's flexible motion. Finally, the observer operation characteristic curve is constructed to obtain the separation result of UAV positioning signal. By mapping the information entropy data in the high dimensional space, the artificial intelligence technology realizes the extraction and separation of UAV positioning signal. In the process of UAV positioning using mobile UAV signals, it is impossible to separate the reflected signals of UAV due to the lack of directionality, low power, low sampling rate and complex environmental noise [3]. In the open environment, there is no barrier such as wall, so the UAV reflected signal received from the base station can be divided into three parts, UAV reflected direct wave signal, multipath interference signal and Gauss noise signal. Therefore, the UAV positioning signal model is established as follows:

$$\hat{y} = Py + m\sum_{m=1}^{M} e_m + N_m \tag{1}$$

In formula (1), e_m is the receiving signal, y is the direct wave signal reflected by the UAV, N is the m multi-path interference signal caused by non-line-of-sight factors, and P is the noise error. After analyzing the signal delay and phase shift in the process of UAV positioning signal propagation, the formula (2) can be refined as follows:

$$\hat{y}(t) = \alpha_0 F\cos(\theta_0) + \hat{y}\sum_{m=1}^{M} \alpha_m F \tag{2}$$

After analyzing the model and the actual test data, it is found that α_0 and N can not separate the positioning signal based on signal power or phase because of the low F

base station power and the small α_0 of UAV. The momentum principle can improve the convergence speed of the adaptive learning algorithm, and provide a new way to improve the performance of the localization signal separation algorithm. But the application of momentum technology in localization signal processing is still at the exploratory stage, and its theoretical and practical effects still need to be further extended and improved. First, the accuracy and rationality of momentum factor selection have an impact on the convergence performance of the learning algorithm. Secondly, in the design of the gradient algorithm, how to make the momentum item and learning steps can be used reasonably and cooperatively, so as to make the algorithm achieve the best performance [4]. These are the problems to be solved to some extent in the future. In order to solve this problem, the information entropy of UAV is taken as the kernel function and mapped in high dimensional space to complete the UAV positioning signal acquisition.

2.3 Denoising of Fixed Wing UAV Positioning Signal

Fixed-wing UAVs carry image sensors and laser imaging sensors, which cannot fly along the prescribed route due to the influence of air flow and propeller in the course of operation. When the UAVs carry out positioning, the deviation of fine pitch angle, yaw angle and roll angle is produced. At the same time, the continuity of the positioning process is limited and the target position cannot be accurately located. Fixed-wing UAV can capture the origin of take-off coordinates in the range of view, establish coordinate system, so that the fixed-wing UAV in the range of view can accurately capture the target after flying for a certain distance, then complete image processing and recognition, and then locate the target position. After coordinate system conversion, the remote sensing positioning model of fixed-wing UAV can be obtained as shown in Fig. 2.

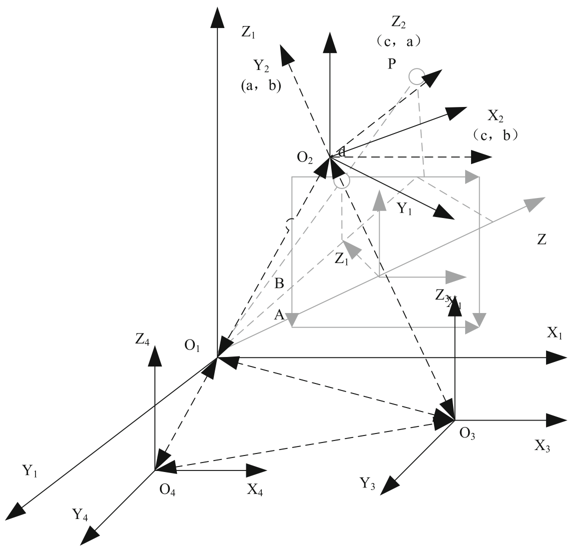

Fig. 2. Fixed wing UAV positioning model

From Fig. 2, the latitude and longitude information is confirmed by the fixed-wing UAV remote sensing images, where a, b and c show the deviation of the fixed wing UAV from the slight pitch, yaw and roll angle caused by the air flow and propeller respectively. For the sensor selection of electromagnetic field sensor, most of them use three-axis orthogonal ECG or three-axis orthogonal ECG or magnetoresistive sensor as sensors, and some of them use Hall sensor or magnetoresistive sensor to show the measuring range of all kinds of sensors. It can be seen from the diagram that the induction coil or inductor can be used for detection within a large range of magnetic field intensity [5]. The disadvantage of using coil as electromagnetic field sensor is that the volume and weight of the sensor chip is larger than that of the magnetoresistive sensor chip. But considering that the coil is easy to make, only enameled wire is needed to wrap around the frame.

According to the artificial intelligence positioning model, the target combined with laser imaging and TV image can be located, the pixel coordinate position can be obtained by coaxial TV image, and the target coordinate position can be detected by fixed-wing UAV. Most of the existing adaptive localization signal separation algorithms belong to gradient algorithms. The main disadvantage of these algorithms is that their convergence rates are not satisfied in some real-time applications. In order to improve the convergence performance of the BSS algorithm, this paper proposes a localization signal separation algorithm based on the minimum mutual information criterion and the momentum learning principle [6]. Firstly, a localization signal separation cost function based on minimum mutual information criterion is introduced. Based on the natural gradient principle, the adaptive updating rules with recursive structure including momentum terms are derived. In addition, many existing BSS algorithms can only separate source signals with the same fourth-order cumulant (gradient) symbol. When a fixed-wing UAV has a posture error, the target position shall be corrected, and the result shall be:

$$\begin{cases} A = A'\hat{y}(t) - (Z - zDc) \\ B = B' + P(yDb + xDa) \end{cases} \tag{3}$$

In formula (3), Δa, Δb, Δc represents the random error caused by deviation from the route respectively, and A' and B' represents the real-time feedback of target position information parameters through remote sensing technology. In order to ensure the normal operation of the deployment of a variety of specific business needs, fault location as the core function to meet the emerging characteristics, based on this further build UAV heading location structure as shown in Fig. 3.

Based on the structure, the UAV positioning information is collected and managed, and the positioning points of the preset position are designed to realize signal separation. In addition to the above linear mixed model, the problem of location signal separation under nonlinear mixed model is also studied. A nonlinear localization signal separation method based on perceptron model is proposed for reversible nonlinear hybrid systems. A three-layer perceptron network is used to construct a nonlinear separation system to separate the source signals. The maximum output information angle is used as a separation criterion to adjust the parameters of nonlinear separation system. In the unsupervised adaptive learning of perceptron separation system, it is necessary to adjust three parameters: the weight matrix of hidden layer and output layer, the threshold vector of

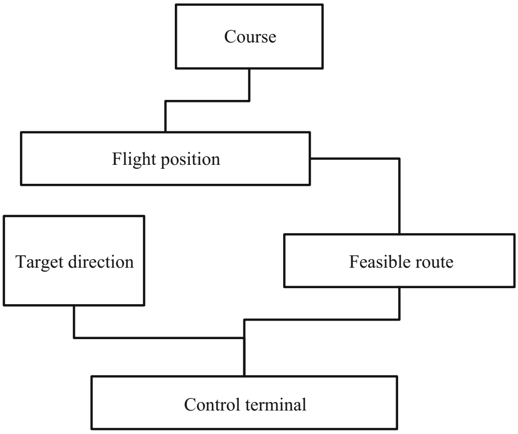

Fig. 3. Schematic diagram of UAV positioning information management structure

neural node. In order to improve the training speed, a conjugate gradient optimization algorithm is introduced to train the weight matrix of the perceptron network. In addition, the Sigmoid function is chosen as the probability distribution function of the separated signal, and an adaptive parameterized probability density estimation method is used to estimate it [7]. By computer simulation, it can be seen that the signal interference ratio of the separation result can reach about 25 dB when the signal mixing process is not instantaneously completed, that is, when the delay of the source signal in the transmission process of the sensor is taken into account, the mixed model of the location signal separation problem is transformed into a convolved mixed model of multi-dimensional signals. A joint approximate diagonalization method for the separation of linear convolution mixed signals is proposed. First, the convolution mixed model is transformed into an instantaneous mixed model to obtain a new instantaneous mixed signal.

2.4 Implementation of UAV Positioning Signal Separation

2.4.1 Positioning Point Layout of UAV TT & C Preset Position

With the development of the research on location signal separation, the research on BSS focuses on two aspects: the choice and exploration of cost function and the design of different optimization algorithms. On the basis of the previous section, this section proposes a well-posed hybrid model localization signal separation algorithm based on conjugate gradient optimization algorithm. The algorithm is still based on mutual information, and the conjugate gradient algorithm is used to search the separation matrix. As the key to the success of the algorithm, the kernel probability density estimation method is used to estimate the probability density and its derivative of the separated signal. Instead of selecting a single nonlinear activation function based on experience, the effectiveness of the proposed algorithm is verified by computer simulation. Set up Q_1, Q_2 and Q_3 to represent respectively the first type of data information, the second type of data information and the third type of data information. Combined with the above physical quantities, the definition of the preset stage of UAV measurement and control can be expressed as follows:

$$E = \frac{\sqrt{\left(xQ_1^2 + yQ_2^2 + zQ_3^2\right) - \hat{y}(t)}}{|A + B|\cos(\theta_0)} \tag{4}$$

According to the structural characteristics of different predetermined stages, the orientation of the orientation vectors in the action coordinate system is planned. In the weighted hyper-positioning coordinate system, A_0 represents the initial position information of the preset position for UAV measurement and control, and A_n represents the completion position information of the preset position for UAV measurement and control, In the simultaneous formula, the principle of overall planning of the positioning points of the preset position may be expressed as follows:

$$\overrightarrow{A_0A_n} = \int_0^n \frac{\beta^2|A_n \times A_0|^2}{E\dot{u}} - E \tag{5}$$

In formula (5), $\overrightarrow{A_0A_n}$ represents the UAV marker vector from the initial position to the completion position, n represents the specific actual value of the UAV TT&C preset position from the initial position to the completion position, β represents the given curvature condition of the navigation curve in the weighted hyper-positioning coordinate system, and $\dot{u}$ represents the planned regression coefficient within the TT&C navigation path. On the premise that the overall planning position of the preset position remains unchanged, taking the given time T as the counting condition, from all possible curvature values in the weighted overposition coordinate system, a vector is randomly selected to be defined as β', and R_0 is set to represent the boundary parameters of the lower bound layout, and R_1 represents the boundary parameters of the upper bound layout, and the simultaneous formula, so that the positioning point layout discriminant of the preset position of the UAV can be expressed as follows:

$$W = \frac{\left|1 - \beta' \sum_{R_0}^{R_1} T \cdot \overline{p}^2\right|}{\chi' \left|\overrightarrow{A_0A_n}\right|} \tag{6}$$

In formula (6), $\overline{p}$ represents the average navigation speed of the UAV measurement and control device in the weighted over-positioning system, and χ' represents the layout permission parameters of the positioning points.

2.4.2 Obtaining UAV Positioning Data

Calculate the Euclidean distance between any two A and B data samples according to the original data set. If B is within the radius of A, connect A and B, set the length of the connecting line to d; if not within the radius, set the length of the connecting line to ∞. This repetition constructs the UAV's undirected course location primitive dataset, as shown in Fig. 4.

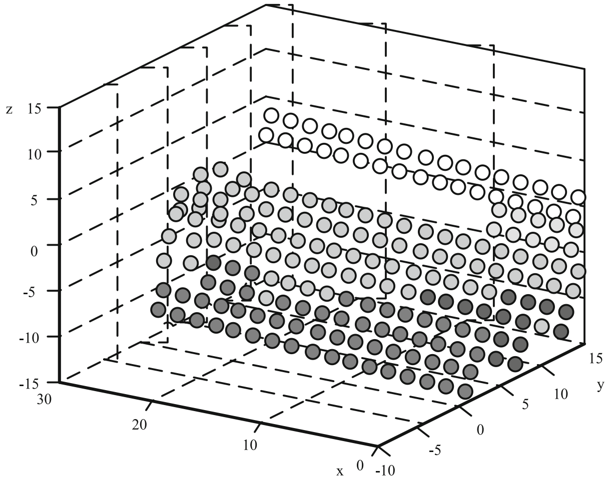

Fig. 4. Original dataset of UAV heading localization

The shortest distance between any two samples is further calculated, and the shortest distance d_1 between any two data in the original data set is calculated by using the Isomap algorithm. The shortest distance matrix obtained therefrom is:

$$d' = \mathrm{W} - \overrightarrow{A_0}A_n\{d_1(A, B)\} \tag{7}$$

Because the shortest distance obtained by the above formula is affected by noise, the calculation of distance is not accurate. Therefore, the Isomap algorithm is applied to the distance matrix of the formula:

$$D = d'^2 = \left\{d_1^2(A, B)\right\} \tag{8}$$

Since the distance matrix has smooth sample data, we need to use nonlinear dimensionality reduction method to obtain the dimension of the sample data, but this process will be disturbed by noise, so the original data will be distorted in the dimension reduction space. So we use the Isomap equidistant feature mapping method to reduce the dimension, and the reduced dimension and denoised heading data is shown in Fig. 5.

According to the data set after dimensionality reduction and noise reduction, the long-range navigation can be located in real time to ensure the effectiveness of the design.

2.4.3 Calculate the Distance Between Execution Tracks

In the process of execution, there are a lot of redundant test cases, which form a lot of redundant information and reduce the positioning accuracy. Similar execution trajectories of test case execution can be used to accurately locate multiple bugs in a program. The smaller the distance between execution tracks, the more similar the execution tracks, and the multi-valued vectors can be sorted according to the value of vector elements.

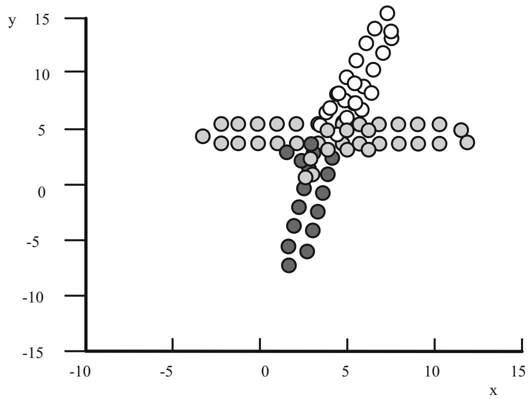

Fig. 5. Course positioning data after dimension reduction and noise reduction

The distance between execution paths is obtained by calculating the number of interconversion steps. Because the selected trajectory can only focus on locating the relationship between new blocks, it is necessary to calculate the distance between the execution trajectories. Set the execution track as follows:

$$\begin{aligned} w_1[j] &= (sus_3, sus_4, sus_1, sus_2, sus_5, sus_6) \\ w_2[j] &= (sus_1, sus_2, sus_5, sus_6, sus_3, sus_4) \end{aligned} \tag{9}$$

Direct use of the number of times parameter calculation is greatly affected by the new block cycle, timely detection of the relative relationship between the number of executions, can fully reflect the similarity between the execution trajectories. According to the coordinates, the new positioning blocks are sorted from near to far, and are numbered sequentially. The new positioning blocks are graded according to the actual defect number, and the higher the score, the higher the positioning accuracy. If the reported score exceeds 90 points, it means that only 10% of the new location blocks need to be audited to quickly locate the defect in the software. The formula is:

$$s = \frac{p - q}{w_1[j] - w_2[j]} - D \tag{10}$$

In formula (10), p represents the total number of new positioning blocks, and q represents the separation result of new positioning blocks. Based on this, the target of fixed wing UAV can be separated and the navigation and positioning accuracy of UAV can be ensured. Artificial intelligence technology has been widely used in the field of location signal separation. In general, this method can be used to solve some instantaneous and convolution mixed BSS problems effectively, but sometimes the separation matrix is singular, so the desired separation signal can not be obtained. In this paper, a joint diagonalization method for location signal separation problem based on artificial intelligence is proposed. The method first transforms the convolution mixture model into an instantaneous mixture model, then divides the transformed signal samples into several groups and obtains the second-order statistics matrix of each group. Finally, a joint diagonalization method is applied to the matrix composed of the second-order statistics matrix to obtain the separation matrix, and a constraint term is introduced to construct the separation cost function of the positioning signal, which avoids the situation that the obtained separation matrix is singular. Simulation results show that the proposed algorithm can effectively separate convolution mixed speech signals. Compared with other convolution mixed-location signal separation algorithms, convolution mixed-location signal separation algorithm can achieve better performance. Nowadays, convolution mixed-location signal separation problem will be met in many applications.

3 Analysis of Experimental Results

In order to test the validity of the fault location algorithm of UAV, the experiment was carried out. Experiment is established in the MATLAB environment, in which the hardware environment for Intel Core 3–550 1 GB of memory, operation for Windows 7. Assuming that a large number of UAV nodes are located in 2000 m $\times$ 2000 m uniform array area. The range of various magnetic field positioning information measurement sensors and experimental parameter settings are shown in Tables 1 and 2.

Table 1. Range of Magnetic Field Positioning Information Sensors

Sensor positioning technology	Approximate detection range
Induction coil sensor	$le - 8$—$le9$
Fluxgate sensor	$le - 6$—$le3$
Optically pumped alkali sensor	$le - 8$—$le2$
Atomic motion sensor	$le - 8 - le2$
SQUID sensor	$le - 9$—$le3$
Hall Effect Sensor	$le0$—$le4$
Magnetoresistive sensor	$le - 6$—$le2$
Bulk transistor sensor	$le - 1$—$le7$

Table 2. Experimental parameter settings

Parameter	Remarks
UAV frequency band	3 kHz–8 kHz
Carrier frequency time width	3 ms
Data initial frequency	0.15 Hz
Number of sampling points	256
Signal to noise ratio variation range	−15 dB–15 dB

According to the experiment environment and the result of parameter setting, the experiment content is analyzed. In order to mine the fault data of UAV, it is necessary to sample the time series of the data, and the waveform of the position information obtained is shown in Fig. 6.

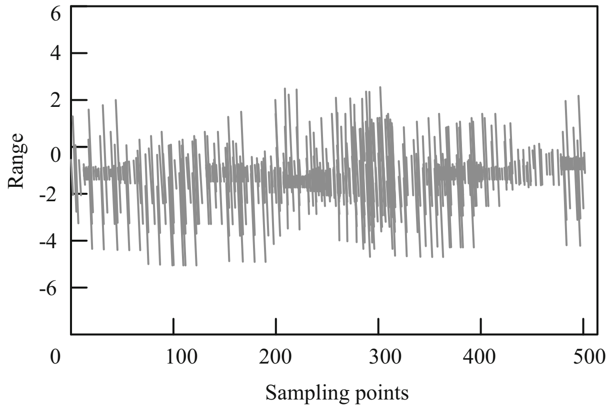

Fig. 6. UAV positioning information waveform

According to the UAV data shown in the graph, the training set is constructed, the fault data mining is tested, and the fault data is analyzed in time domain. Set the default UAV parameters as shown in Table 3.

Table 3. Default Values for UAV Parameters

UAV type	Wavelength	Refractive index	Scattering coefficient scattering coefficient
Single mode	1220 nm	1.521300	−80.0 dB
	1120 nm	1.467200	−83.0 dB
Multimode	1120 nm	1.485000	−72 dB
	450 nm	1.523000	−68 dB

Furthermore, the UAV is taken as the ultimate target, comparing the error elimination results of the technology of reference [1] with the Paper technology, the calculation results of UAV positioning signal separation are shown in Table 4.

It should be noted that the data matrix of positioning signal is always non-negative, so in order to apply the algorithm of UAV positioning signal separation based on artificial intelligence, we need to normalize it to the data of zero mean and unit variance. At the same time, in order to visualize the result of the separation image, the mean and variance of the original signal are recorded. When the separation process is complete, the separation results need to be changed, so that the previously recorded mean and variance data can be restored, while the integer. By further comparing the processing errors with the method of reference [1] and the paper method, and the detection results are shown in Fig. 7.

Table 4. Calculation results of UAV positioning signal separation

Method	Coordinate axis	Maximum	Minimum value	Average value	Error range
Standard coordinates	Axis X	34053	32889	33471	1164
	Axis Y	18113	17432	17772.5	681
	Axis Z	401	−221	90	622
The technology of reference [1]	Axis X	31059	29885	30472	1174
	Axis Y	15442	14381	14911.5	1061
	Axis Z	905	250	551	654
Paper technology	Axis X	34091	33002	33546.5	1089
	Axis Y	17992	16851	17421.5	1141
	Axis Z	398	−198	298	596

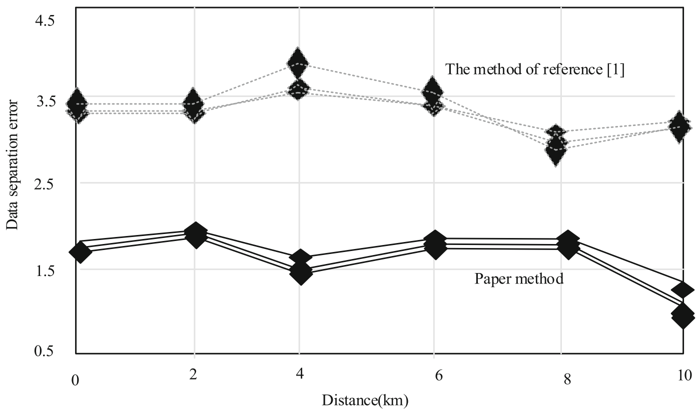

Fig. 7. Signal classification error rate detection results

Compared with the method of reference [1], the proposed algorithm based on artificial intelligence has higher accuracy in the practical application and can fully meet the research requirements.

4 Conclusion

The main problem of passive location of outdoor fixed-wing UAV in multi-path environment is that the UAV location signal can not be separated from noise. A positioning signal separation algorithm for UAV based on artificial intelligence is proposed. By obtaining the information entropy of the original signal, the Euclidean distance is used to balance the data to ensure the validity of the data. When information entropy is used as reference value of positioning information, the positioning signal is processed to reduce space complexity and improve the real-time performance of UAV positioning model.

Combining the information entropy and signal power logarithm, the ROC plane is constructed to realize the separation of the UAV positioning signal by artificial intelligence technology.

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