



# Application of fuzzy probability factor superposition algorithm in nuclide identification

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## Abstract

In this study, a dynamic nuclide identification algorithm based on fuzzy probability factor superposition (FPFS) was proposed for  $\gamma$  spectrum analysis, and the algorithm was tested with spectra from single and multiline radionuclides of the five nuclides  $^{241}\text{Am}$ ,  $^{133}\text{Ba}$ ,  $^{137}\text{Cs}$ ,  $^{60}\text{Co}$ , and  $^{152}\text{Eu}$ . The test results showed when the number of probability factors superposed exceeded 15, the nuclide identification accuracy rate was over 98%. In contrast to the traditional fuzzy logic nuclide identification algorithm and multiple linear regression fitting algorithm, the FPFS algorithm had a higher recognition rate and more advantages especially when there were lower counts and mixed nuclides.

**Keywords** Qualitative analysis · Fuzzy logic · Membership function · Feature extraction · Low count energy spectrum · CZT detector

## Introduction

In many application scenarios such as vehicle-mounted radiation detection or drone-borne detection, the activity of the radioactive source is very small or the detection distance is generally larger. Thus, the count rate of the  $\gamma$  spectrum detected by the detector is low and the characteristic peak is weak [1]. In particular, CdZnTe (CZT) detectors, which are currently widely used in portable detection systems, are small in size and have a lower count rate than larger scintillator detectors. For example, the count rate of the CZT detector used in this experiment (the volume is  $10 \times 10 \times 5 \text{ mm}^3$ ) is only  $\sim 15\text{cps}$  under the background [2, 3]. In these application scenarios, the statistical fluctuations of the  $\gamma$  spectrum are very large, and the characteristic peaks are unstable. The recognition efficiency of traditional nuclide identification algorithms based on characteristic peaks is very contingent and cannot achieve the expected results [4, 5]. Therefore, the rapid detection and qualitative analysis of gamma energy spectrum under low count conditions can greatly improve the application capability and scope of CZT detectors.

A  $\gamma$  energy spectrum analysis method has a wide application prospect, especially the rapid identification algorithm of nuclides under the condition of low counts. In 2002, Eiji Yoshida et al. applied the neural network to the  $\gamma$  energy spectrum analysis obtained by a Ge detector, and successfully realized the isotope identification [6]; In 2013, K Peter et al. used machine learning for nuclide identification and achieved a good nuclide identification effect by using optimization technology for feature peak positioning [7]; In the same year, Miltiadis Alamaniotis et al. proposed to apply a fuzzy logic-based nuclide identification algorithm to radioactive source search and compared it with the maximum likelihood fitting algorithm, which showed a better effect [8–10]. In 2016, C Bobin et al. proposed a real-time processing method based on artificial neural networks and Bayesian rules for the rapid identification of radionuclides [4]. At present, many nuclide recognition algorithms have been developed based on various calculation and statistical tools, especially the development of nuclide recognition algorithms based on full-spectrum features such as artificial neural networks [11–15], naive Bayes [16, 17], and support vector machines [18, 19], which have significantly improved the efficiency of nuclide recognition. However, under low count conditions, the  $\gamma$  spectrum characteristics are not obvious and are easily submerged by other background peaks, and the recognition accuracy of the nuclide recognition algorithm is easily reduced due to the influence of statistical

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fluctuations [20]. The existing algorithms cannot achieve stable and accurate recognition through a single recognition.

This work proposes a fast nuclide identification algorithm based on fuzzy logic and probability factor superposition (FPFS). This method uses the fuzzy logic algorithm to determine the probability factor of the existence of nuclide in each spectrum and eliminates the randomness of single identification by accumulating the probability factors of multiple  $\gamma$  spectra. In the gamma spectrum, peaks from statistical fluctuations such as noise are randomly distributed, and will not exist stably in the gamma spectrum of multiple consecutive measurements. By giving the attenuation factor, the probability factor of the peak position will be maintained at a low level during the accumulation process. The characteristic peak of a nuclide is relatively stable, and the probability factor of its peak position will gradually increase as the number of accumulation increases. After the probability factor has accumulated to a certain extent, the identification of the nuclide can be realized. Through the analysis and test of the measured spectrum obtained by the CZT detector, under low count conditions, the algorithm has a higher recognition rate for multi-nuclide spectra, and the recognition rate is significantly enhanced with the increase of the number of superpositions.

## Methods and experiments

The fast radioisotope identification algorithm proposed in this paper is mainly divided into three steps, as shown in Fig. 1.

First, fast feature extraction. The potential peaks can be obtained by feature extraction. The feature extraction algorithm is required to be simple, fast, and sensitive to possible peaks.

Second, probability factor calculation. Fuzzy logic rules are used to match the preliminary peak searching results with the nuclide library to obtain the probability factors of different characteristic peaks of a single spectrum.

Finally, radioisotope identification. By accumulating the probability factors of multiple energy spectra measured continuously over time, more accurate radioisotope identification results can be obtained.

### Fast feature extraction

For the identification of radioactive isotopes, the most obvious feature is the characteristic peaks formed in the energy spectrum of the gamma rays with specific energy emitted by the nuclide. Accurate feature extraction results can greatly improve the possibility and accuracy of radioisotope identification. To take into account the simplicity of the algorithm and the compatibility with the fuzzy logic isotope recognition algorithm, this work proposes an adaptive window maximum comparison algorithm for feature extraction. The steps in the adaptive window maximum comparison algorithm are shown in Fig. 2.

The algorithm firstly judges whether the count of the candidate channel is the maximum value of the count of each channel in the window. If it is the maximum value, the count of the candidate channel is compared to a threshold value in its spectral neighborhood. We define the spectral neighborhood of a peak as  $2N + 1$  channels and  $N$  is related to the resolution of the detector, and it can be calculated by the following formula:

$$N = \text{ceil}(i * \text{res}) + 2 \quad (1)$$

where  $\text{ceil}()$  means rounding up the data,  $\text{res}$  is the resolution of the detector. A channel is identified to be a potential peak if the number of counts in this channel is the maximum value in its neighborhood and greater than the threshold value  $T$ .  $T$  is calculated by the following formula:

$$T = \text{ave} + \sigma \quad (2)$$

In the formula,  $\text{ave}$  represents the average value of the counts of each channel in the window and  $\delta$  is the standard deviation of the counts of each channel in the window.

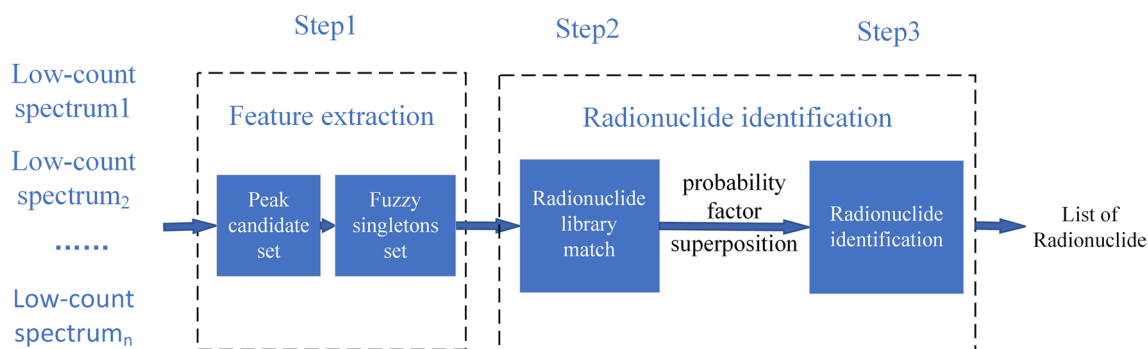
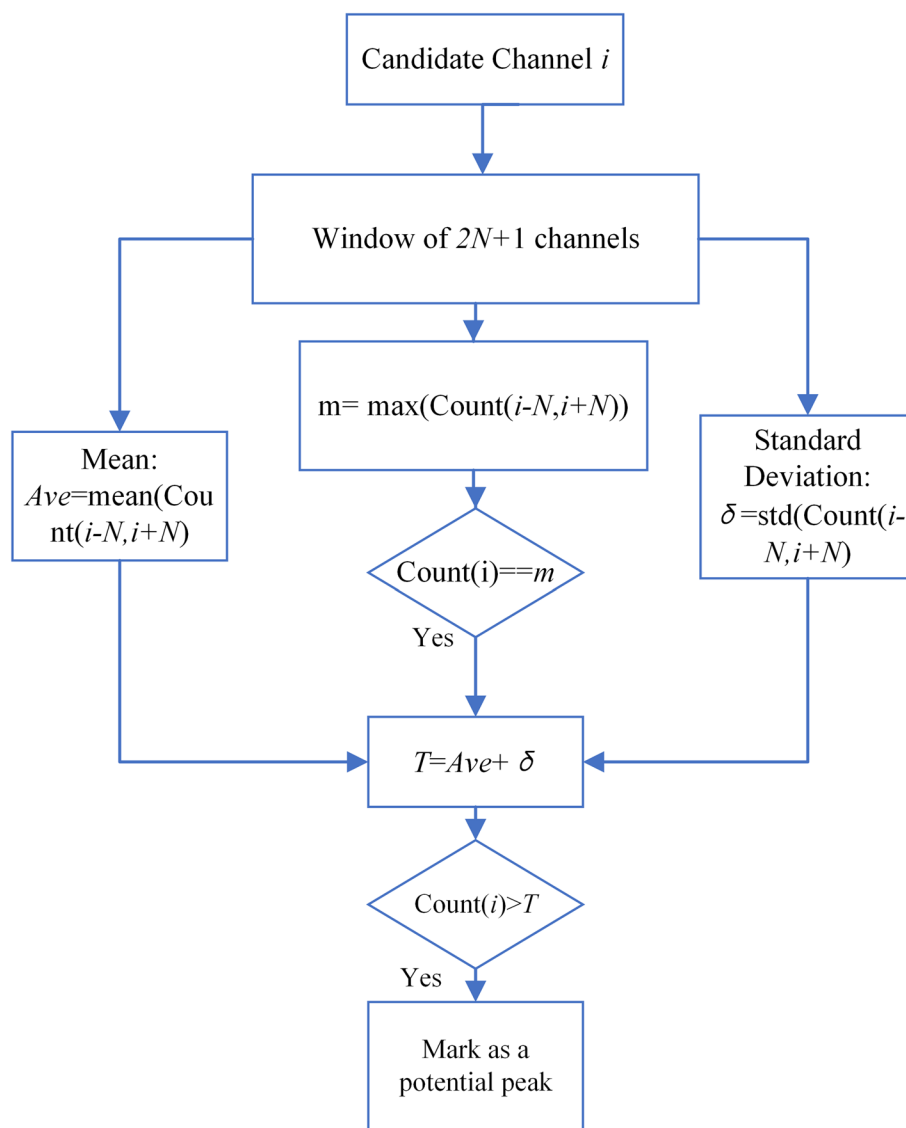


Fig. 1 Block diagram of the FPFS algorithm for analysis of low-count spectra

**Fig. 2** The block diagram of Feature extraction

According to the resolution characteristics of the detector, the width of the comparison window gradually increases with the increase of energy, so that it can better match the widening of the peak position. Experiments show that this method is more sensitive to the weak peaks of real nuclide characteristics and eliminates some low-frequency noise effects.

After feature extraction, the potential peaks is further transformed into a fuzzy singleton representation:

$$\begin{cases} \mu_s(i) = 1 & \text{potential peak} \\ \mu_s(i) = 0 & \text{non - potential peak} \end{cases} \quad (3)$$

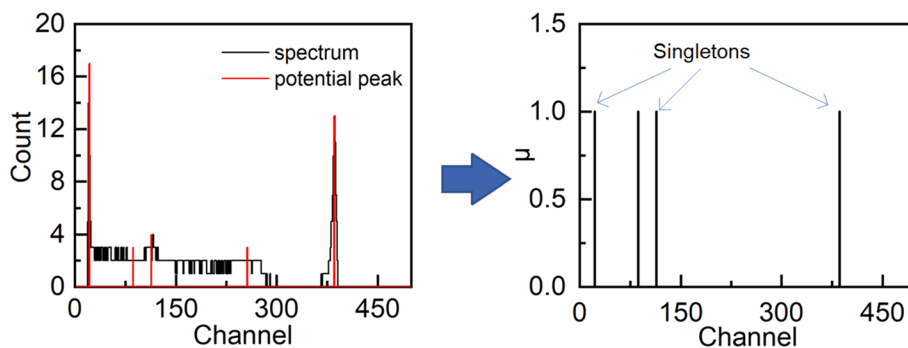
As shown in Fig. 3, the output of fast feature extraction is a set of fuzzy logic singletons containing all potential peaks

$$S = \{(i, \mu_s(i) = 1)\} = \{(i, 1)\} \quad (4)$$

### Calculation of probability factor

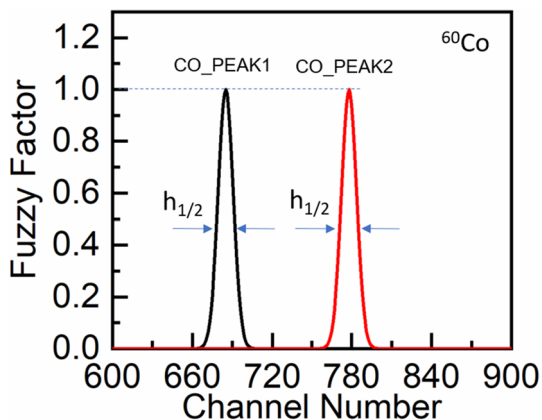
Through many experiments, it has been found that under the condition of low count, due to the influence of statistical fluctuations and other factors, the peak positions of  $\gamma$ -rays with certain energy and intensity in the energy spectrum are random, and generally distributed according to the normal distribution law. The broadening of the distribution is related to the detector resolution. Therefore, in this experiment, we use the gaussian membership function to define the membership degree of the characteristic peaks of nuclides and construct a nuclides template library. The radionuclide library contains eleven radionuclides commonly found in industry and nature [21]. Table 1 lists these eleven radionuclides and gives the more obvious characteristic gamma-ray energy in the energy spectrum of each nuclide.

**Fig. 3** The result of feature extraction is transformed into fuzzy singlet



**Table 1** Description of the measured spectrum test set

Radionuclides	Gamma ray energy	Radionuclides	Gamma ray energy
<sup>241</sup> Am	59.54 keV	<sup>152</sup> Eu	121.78 keV, 244.70 keV, 344.28 keV
<sup>133</sup> Ba	81 keV, 302.85 keV, 356.01 keV	<sup>40</sup> K	1460.82 keV
<sup>60</sup> Co	1173.23 keV, 1332.49 keV	<sup>226</sup> Ra	186.211 keV
<sup>57</sup> Co	122.06 keV	<sup>192</sup> Ir	295.96 keV, 308 keV, 316.506 keV, 468.069 keV
<sup>137</sup> Cs	661.66 keV	<sup>232</sup> Th	59 keV, 126 keV
<sup>75</sup> Se	121.12 keV, 136 keV, 264.66 keV, 279.54 keV	–	–



**Fig. 4** Distribution of <sup>60</sup>Co peaks positions and probability factors in the fuzzy logic nuclide library

Figure 4 shows the distribution of nuclide peak positions and membership degrees of <sup>60</sup>Co peaks, where each peak corresponds to a characteristic peak position [8]. The membership degree of the *j*-th characteristic peak of the *i*-th nuclide at the *x*-th channel can be calculated by the following formula:

$$\mu_{ij}(x) = e^{\frac{-(x-p_{ij})^2}{2*(h_{1/2})^2}} \tag{5}$$

where  $P_{ij}$  represents the *j*-th characteristic peak position of the *i*-th nuclide in the nuclides template library.  $h_{1/2}$  is full width at half maximum of the fuzzy logic gaussian membership equation. The value of  $h_{1/2}$  is related to specific application scenarios. To reduce the interference of adjacent peaks, the value of  $h_{1/2}$  should match the actual measurement peak as much as possible. The resolution of the CZT detector is 1.4% at 661.66 keV and changes with energy, So the value of  $h_{1/2}$  was set to the product of the channel and the corresponding energy resolution:  $P_{ij} \times res$ .

The probability factor of the *j*-th characteristic peak of the *i*-th nuclide at the *x*-th channel can be calculated by formula (6).

$$f_{ij}(x) = \mu_s(x) \cdot \mu_{ij}(x) \tag{6}$$

In the formula,  $\mu_s(x)$  refers to the fuzzy singleton value, which is calculated by formula (3).

**Radioisotope identification**

The radioisotope identification module mainly adopts the method of superposition of probability factors, which is similar to the ant colony algorithm [22]. In the application of

radionuclide identification, each channel of the  $\gamma$ -ray spectrum was regarded as a path. The probability factor derived from the fuzzy logic algorithm is regarded as a “pheromone” [23]. When a certain channel address may have a potential peak, the channel will leave a corresponding probability factor, and the probability factor will increase with the superimposition of the spectrum. In the continuously collected gamma-ray spectrum, if the probability factor of a certain channel is equal to zero, then the probability factor of the channel will gradually decrease until it reaches zero (“pheromone” volatilization). In this experiment, the volatilization rate of probability factor is set to  $-0.3$  through actual test and optimization.

$$F_{ij}(x) = \sum_{d=1}^T f_{ij}^d(x), x = 1, 2 \dots N, f_{ij}^d(x) = \begin{cases} f_{ij}^d(x) f_{ij}^d(x) > 0 \\ -0.3 f_{ij}^d(x) = 0 \end{cases} \quad (7)$$

In the above equation,  $F_{ij}(x)$  is the probability factor of the  $j$ -th characteristic peak of the  $i$ -th nuclide at the  $x$ -th channel after  $T$  times of superposition, and  $f_{ij}^d(x)$  is the probability factor of the  $j$ -th characteristic peak of the  $i$ -th nuclide of the  $d$ -th  $\gamma$ -ray spectrum at channel  $x$ . With the increase of iteration times, the probability factor of the nuclide peak position will increase, while that of noise peaks will remain at a very low level.

Then the probability factor of the  $j$ -th characteristic peak of the  $i$ -th nuclide can be calculated by the following formula:

$$F_{ij} = \sum_{x=x-h_{1/2}}^{x+h_{1/2}} F_{ij}(x) \quad (8)$$

After calculating the probability factor, nuclide matching is required. For multi-feature peak nuclides, each feature peak can be given a weight  $w_j$  according to the significance of each feature peak, that is, the  $\gamma$ -ray branching ratio of the corresponding energy and the sensitivity of the detector to the corresponding energy. The probability factor of the existence of the  $i$ -th nuclide can be calculated by formula:

$$F_i = \sum w_j F_{ij} \quad (9)$$

If  $F_i$  is greater than the threshold, the  $i$ -th nuclide exists. For nuclides with only one characteristic peak, it is first necessary to determine whether there are interfering nuclides with similar energies in fuzzy logic nuclide library, for example,  $^{57}\text{Co}$  that emits a gamma ray at 122.06 keV that is interfering with the 121.78 keV gamma ray from  $^{152}\text{Eu}$  and the 121.12 keV gamma ray from  $^{75}\text{Se}$ . If there are mutual interfering nuclides, the probability factor of mutual interfering nuclides needs to be calculated at the same time. The results can be divided into three cases: (1) The current nuclide probability factor is less than the threshold, which can be directly excluded; (2) The current nuclide probability factor is less than the threshold, but the probability factor of the mutual interference nuclide is less than the threshold, and the existence of the nuclide can be directly determined; (3) If the probability factors of both are greater than the threshold, the algorithm cannot give the result directly, and further quantitative calculation is required. But the algorithm can give the relative value of the probability factor for reference.

### Example case

Taking the analysis of  $^{60}\text{Co}$  and  $^{137}\text{Cs}$  superposition spectrum as an example to illustrate the FPFs algorithm. The measurement time of each  $^{60}\text{Co}$  spectrum is 1 s and fifteen spectra were collected continuously. The measured spectrum is shown in Fig. 5a, in which the positions of the characteristic peaks of two nuclides,  $^{60}\text{Co}$  and  $^{137}\text{Cs}$ , were marked.

Firstly, the gamma-ray spectrum is given as an input to the feature extraction module. The algorithm locates all the spectral peaks and represents them with fuzzy singletons as described in Section “Fast feature extraction”. Figure 5b, c shows the results of the peak search and the fuzzy singletons. Due to statistical fluctuations, the feature extraction algorithm also identifies many peaks from statistical fluctuations as candidate peaks.

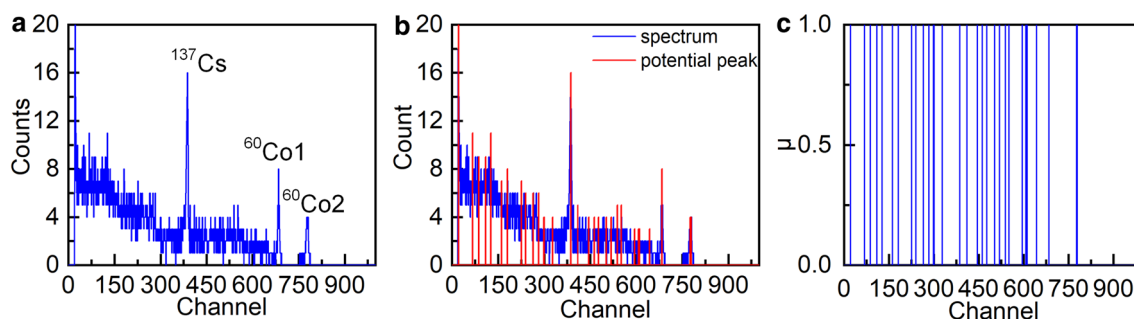


Fig. 5 The result of feature extraction and the fuzzy monomorphic set

In the next steps, the probability factor is calculated by matching the fuzzy singleton set with the fuzzy logic nuclide library. We expect that most of the background peaks will be eliminated. The calculation result of the probability factor is as follows:

$$\begin{aligned}\mu(^{241}\text{Am}) &= 0.368; \mu(^{137}\text{Cs}) = 0.778; \\ \mu(^{60}\text{Co}) &= 0.843; \mu(^{152}\text{Ba}) = 0.04.\end{aligned}$$

Since the peak positions of the peaks from statistical fluctuations coincide with the characteristic peaks of  $^{241}\text{Am}$  and  $^{133}\text{Ba}$ , they are misidentified as characteristic peaks. This is also the reason for the inaccuracy of the nuclide identification algorithm under the low count condition. When FPFS is used for nuclide identification, due to the randomness of characteristic peaks, after 15 stacking, its influence on nuclide identification will gradually decrease. The normalized results of each nuclide probability factor are shown as follows:

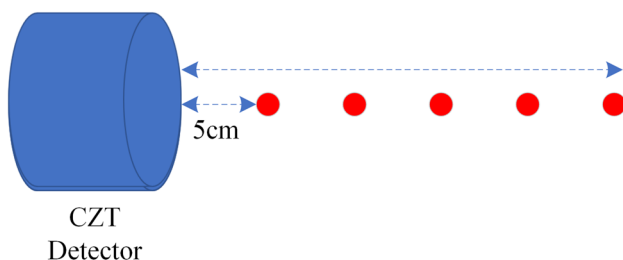
$$\begin{aligned}\bar{\mu}(^{137}\text{Cs}) &= 0.7852; \bar{\mu}(^{241}\text{Am}) = 0.0136; \\ \bar{\mu}(^{60}\text{Co}) &= 0.5865; \bar{\mu}(^{133}\text{Ba}) = 0.0047;\end{aligned}$$

By setting the threshold of 0.2 obtained from the sample statistics, we can confirm that the gamma spectrum came from  $^{137}\text{Cs}$  and  $^{60}\text{Co}$ .

### Experimental system and identification performance evaluation

To evaluate the proposed method, a gamma-ray spectrometry system was established, which consists of a 10 mm\*10 mm\*5 mm CZT detector (Imdetek Inc.) coupled with a multichannel analyzer (MCA) (ORTEC Inc.) along with software GammaVision 8.10.02. The detector was installed at a fixed location, and the radionuclides were placed at different distances from the detector, as shown in Fig. 6. Samples with different times, activities, and distances were obtained. Table 2 lists the radionuclides utilized in the experiment.

The detection rate was used to evaluate the identification performance of the proposed algorithm [24]. The detection



**Fig. 6** Schematic of the experimental detection of radioactive sources

**Table 2** Radionuclides for the experiments conducted in this study

Radionuclide	$^{241}\text{Am}$	$^{133}\text{Ba}$	$^{152}\text{Eu}$	$^{137}\text{Cs}$	$^{60}\text{Co}$
Activity( $\mu\text{Ci}$ )	3.80	1.13	1.03	3.41	3.95

rate is defined by the ratio of the correctly identified data to the total amount of data as shown in Eq. (10)

$$\text{Detection rate (\%)} = \frac{TP}{TP + FP} \times 100 \quad (10)$$

In the formula,  $TP$  represents the number of samples for which the nuclide components contained in the energy spectrum are correctly identified,  $FP$  represents the number of samples that were identified incorrectly, and the sum of  $TP$  and  $FP$  is the total number of samples.

Finally, to test the performance of the proposed algorithm, the results of the developed FPFS algorithm were compared with those of the Multiple Linear Regression algorithm (MLR) [25–27] and Fuzzy logic algorithm (FL) [8, 9].

## Result and discussion

### Analysis of different nuclide superposition spectrum identification

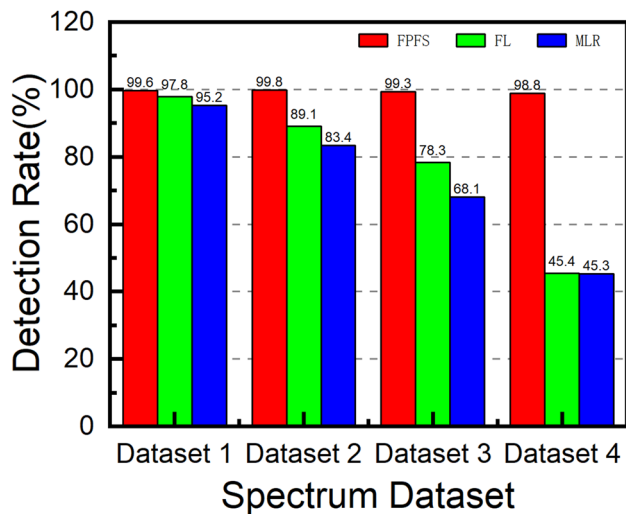
The test set consists of four datasets as shown in Table 3. Each dataset contains 1000 samples, each sample is composed of 30 continuously measured gamma spectra, and the measurement time of each gamma spectrum is 1 s. In the experiment, the number of superpositions of the FPFS algorithm is set to 15 times. To form a contrasting effect, the FL and MLR algorithms analyze the accumulated spectrum of 15 gamma spectra, which is equivalent to directly measuring the gamma energy spectrum with a measurement time of 15 s.

Figure 7 is the result of three kinds of nuclide identification algorithms for different nuclide superposition spectrum nuclide identification. It can be seen from the figure that the detection rate of the three algorithms for the single nuclide spectrum is relatively close, above 95%. However, with the increase of the nuclide component in the gamma spectrum, the performance of the FL and MLR algorithms has decreased significantly. In particular, the detection rates of the two algorithms for the five-nuclides superimposed spectrum are only 45.4% and 45.3%, respectively, while the FPFS algorithm is still keeping it above 98%.

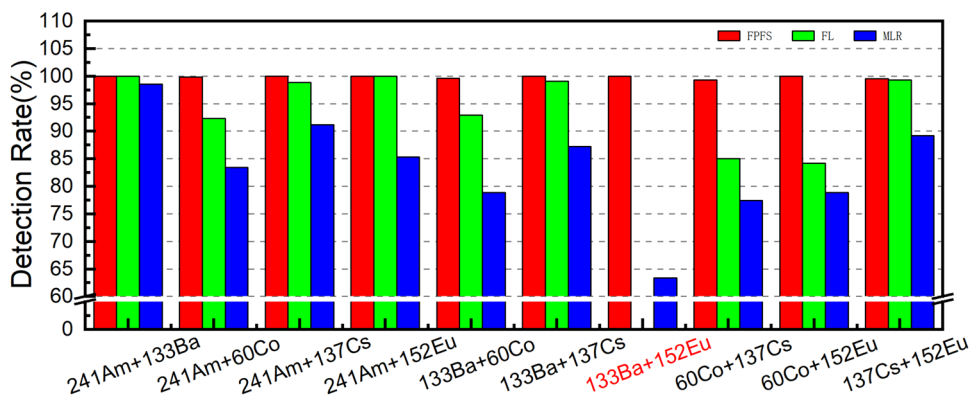
Figures 8 and 9 show the details of the analysis of the two-nuclides superposition spectrum and the five-nuclides superposition spectrum by the three algorithms. In the analysis of the multi-nuclide superposition spectrum, FL

**Table 3** Description of the measured spectrum test set

Test set	Gamma spectrum description (five nuclides $^{241}\text{Am}$ , $^{133}\text{Ba}$ , $^{137}\text{Cs}$ , $^{60}\text{Co}$ and $^{152}\text{Eu}$ were used in the experiment)
Dataset 1	Single nuclide spectrum of the five nuclides
Dataset 2	Superposition spectra of any two nuclides among the five nuclides
Dataset 3	The superposition spectrum of any three nuclides among the five nuclides
Dataset 4	The superposition spectrum of any four nuclides among the five nuclides and five nuclides superimposed spectrum

**Fig. 7** The detection rate of three nuclides identification algorithms on different Dataset

and MLR algorithms are easily affected by nuclides with large statistical fluctuations or nuclides with close characteristic peaks, resulting in a decrease in the recognition rate. Since the two nuclides,  $^{133}\text{Ba}$  and  $^{152}\text{Eu}$ , have a great influence on each other, when the two nuclides exist at the same time, the probability of  $^{133}\text{Ba}$  being recognized decreases rapidly. The accuracy of the algorithm that identifies nuclides through a single judgment is greatly affected by statistical fluctuations. Especially when the peaks from

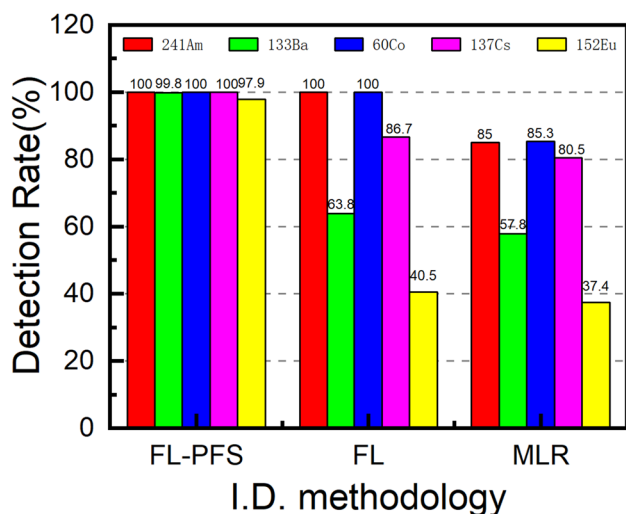
**Fig. 8** The Detection rate of three kinds of nuclides identification algorithm to different double nuclides superposition spectrum

statistical fluctuations coincide with a single characteristic peak nuclide such as  $^{241}\text{Am}$ , or when certain characteristic peaks of multi-character nuclides are submerged by noise, misidentification will occur.

### Analysis of radioisotope identification under different counts

Experiments have proved that for  $\gamma$ -ray spectra with better statistics, especially for nuclides with obvious characteristic peaks and small noise fluctuations, the radioisotope identification algorithm is easier and more accurate to identify this nuclide. Some nuclides have high characteristic peak counts, and the superposition of  $\gamma$ -ray spectra has little effect on the accuracy of the identification of the nuclides. To test the robustness of the radioisotope identification algorithm, the position between the radioactive source and the detector is adjusted to make the characteristic peak counts of the 1 s spectrum of each nuclide close. Four nuclide combinations were selected for testing. The spectrum of radioisotopes with similar characteristic peaks is shown in Fig. 10, and the Identification results are shown in Table 4.

Because the feature extraction algorithm has a high sensitivity to weak peaks, the reduction of the counting rate does not significantly reduce the accuracy of radioisotope identification and remains above 95%.

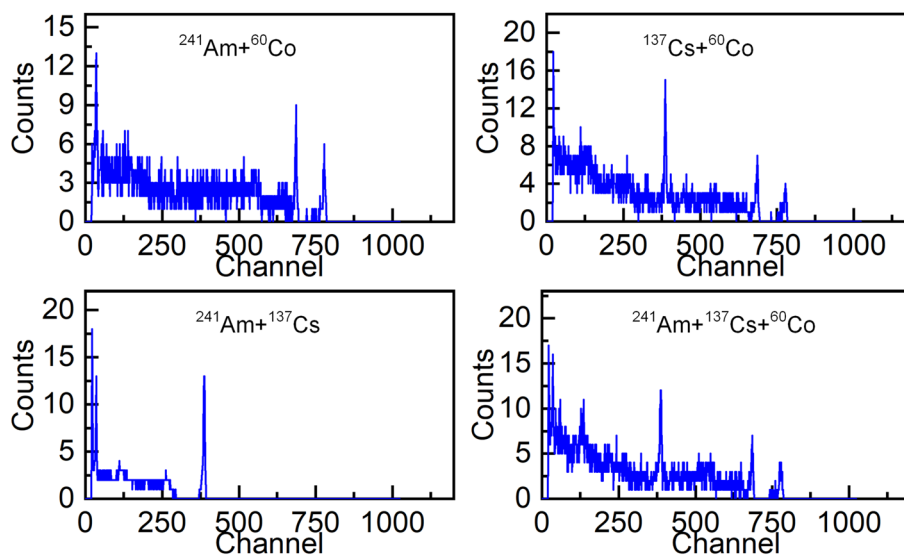


**Fig. 9** The detection rate of different nuclides in the superposition spectrum of five nuclides by three nuclides recognition algorithms

### Probability factor superposition analysis

To study the influence of the measurement time of a single spectrum and the number of superpositions of FPFS algorithm on the accuracy of radioisotope identification, the following two-step experiment was carried out:

**Fig. 10**  $\gamma$  Spectrum of radioisotopes with similar characteristic peaks counts



**Table 4** Identification results of different radioisotope mixing spectra with similar characteristic peak counts

Radioisotope	Average of full-spectrum counts	Detection rate (%)	Probability factor of target nuclide	Probability factors of other nuclides
<sup>241</sup> Am + <sup>137</sup> Cs	728	99.9	0.892	0.002
<sup>241</sup> Am + <sup>60</sup> Co	1948	99.7	0.731	0.008
<sup>137</sup> Cs + <sup>60</sup> Co	2602	99.3	0.623	0.007
<sup>241</sup> Am + <sup>137</sup> Cs + <sup>60</sup> Co	2639	99.9	0.385	0.003

1. Set the number of superpositions of FPFS algorithm to 15, then change the measurement time of a single spectrum, and analyze the performance of the algorithm.
2. Set the measurement time of a single spectrum to 1 s, then change the number of superpositions of the FPFS algorithm, and analyze the performance of the algorithm.

Firstly, the <sup>60</sup>Co spectra and the five-nuclides superposition spectrum with different measurement time of a single spectrum were analyzed. The results are shown in Table 5. The analysis result shows that increasing the measurement time of a single spectrum will increase the detection rate to a certain extent. This is because the influence of random noise on the  $\gamma$  spectrum will decrease as the measurement time of a single spectrum increases, so that the characteristics of the  $\gamma$  spectrum will be enhanced, thereby improving the accuracy of feature extraction. However, the small increase in the measurement time of a single spectrum cannot effectively improve the  $\gamma$  spectrum characteristics, so the effect is not obvious.

Secondly, the single nuclide spectra of <sup>60</sup>Co, the two-nuclide spectra of <sup>60</sup>Co and <sup>152</sup>Eu, and the five-nuclide spectra with the same measurement time of a single spectrum are analyzed by the nuclide identification algorithm with different number of probability factor superposition. The result is



**Table 5** Analysis results of  $\gamma$ -ray spectra with different forming times by dynamic radioisotope identification algorithm

Measured time of a single spectrum	Radioisotope	Detection rate (%)	Probability factor of target nuclide	Probability factors of other nuclides
1 s	$^{60}\text{Co}$	99.1	0.686	0.015
	$^{241}\text{Am} + ^{133}\text{Ba} + ^{137}\text{Cs} + ^{60}\text{Co} + ^{152}\text{Eu}$	98.5	0.551	0.022
2 s	$^{60}\text{Co}$	99.3	0.792	0.015
	$^{241}\text{Am} + ^{133}\text{Ba} + ^{137}\text{Cs} + ^{60}\text{Co} + ^{152}\text{Eu}$	99.0	0.582	0.024
3 s	$^{60}\text{Co}$	99.2	0.812	0.015
	$^{241}\text{Am} + ^{133}\text{Ba} + ^{137}\text{Cs} + ^{60}\text{Co} + ^{152}\text{Eu}$	98.7	0.601	0.023
5 s	$^{60}\text{Co}$	99.4	0.813	0.013
	$^{241}\text{Am} + ^{133}\text{Ba} + ^{137}\text{Cs} + ^{60}\text{Co} + ^{152}\text{Eu}$	98.8	0.632	0.021

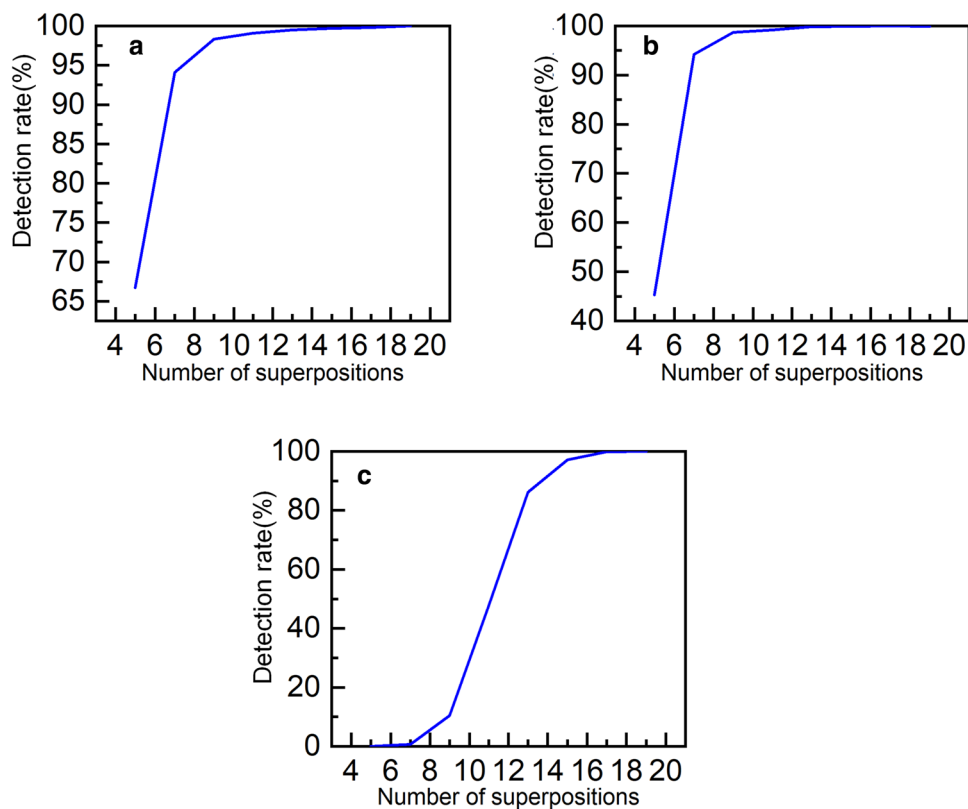
shown in Fig. 11. It can be seen from the figure that increasing the number of superpositions will greatly improve the accuracy of nuclide identification. The efficiency of nuclide identification is more than 95% when the number of stacking times is more than 15 times.

## Conclusion

In this paper, a radioisotope identification algorithm (FPFS) based on fuzzy logic and probability factor superposition is proposed. The method determines the probability factor of the existence of nuclides in each spectral line through the

fuzzy logic algorithm and eliminates the randomness of single measurement identification by superimposing the probability factors of multiple spectra. In the  $\gamma$ -ray energy spectrum, the peaks from statistical fluctuations such as noise are randomly distributed, and will not exist stably in the gamma spectrum of multiple consecutive measurements. By giving the attenuation factor, the probability factor will be maintained at a low value during the superposition process. The characteristic peaks of nuclides are relatively stable, and the probability factor will gradually increase with the increase of the accumulation times. After the probability factor is accumulated to a certain extent, the stable identification of nuclides can be realized.

**Fig. 11** Influence of probability factors superposition times on recognition accuracy: **a**  $^{60}\text{Co}$ ; **b**  $^{152}\text{Eu}$ ,  $^{60}\text{Co}$ ; **c**  $^{241}\text{Am}$ ,  $^{133}\text{Ba}$ ,  $^{137}\text{Cs}$ ,  $^{60}\text{Co}$ ,  $^{152}\text{Eu}$



The FPFS algorithm is verified by measured spectrum obtained by the CZT detector. Experiments show that, compared with the traditional fuzzy logic nuclide identification algorithm (FL) and the multiple linear regression fitting algorithm (MLR), the FPFS algorithm has a higher identification rate for nuclides, especially for multi-nuclide superposition. When the spectra from single and multiline radionuclides is analyzed, the influence of the mutual interference of the characteristic rays of different nuclide energies is small, and the high identification efficiency can be maintained. By analyzing the influence of the measurement time of a single spectrum and the number of superpositions of FPFS algorithm on the accuracy of radioisotope identification, it can be seen that the algorithm can flexibly set superposition times of probability factors according to different application environments and requirements, so as to obtain the required recognition accuracy in the shortest time. The identification results are dynamically updated with the increase of the number of superpositions. Under the condition that the measurement time of a single spectrum is constant, the longer the total measurement time, the higher the confidence of the nuclide identification result.

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