Design of Radionuclides Identification Algorithm Based on Sequence Bayesian Method

Zeqian Wu, Bairong Wang* and Jian Sun
Institute of NBC Defense, Beijing, 102205, China
*Corresponding author’s e-mail: fhwbr@163.com

Abstract. An efficient method of radionuclides identification is essential for the work in the nuclear-related area. In this paper, sequential Bayesian method is embedded into a new radionuclides identification algorithm. Through the process of energy screening, parameter estimation, decision-making function updating and judging, the types of radionuclides can be identified quickly and accurately. This algorithm is tested by using the measured energy spectrum detected by LaBr₃(Ce) detector, and the results are composed of the following four parts for the case where the widths of region of interest are 4σ and 6σ respectively: the selection experiment of two pre-set parameters of the algorithm; false alarm rate and missed alarm rate of radionuclides identification; the effect of energy drift on the identification accuracy; the average number of total collected particles and valid particles needed for identification process.

1. Introduction
With the development of nuclear industry, the word ‘radioactive’ more and more comes into people's vision, which brings new opportunities and challenges for effective method of nuclides analysis.

As an important part of radionuclides analysis, radionuclides identification (RID) is widely used in a variety of scenarios involving radioactivity. For instance: through the detection and RID process near the nuclear power plant, we can know the type of radionuclides it release and whether it will influence the surroundings and residents; In a state of nuclear accident emergency response, a quick and accurate RID method is benefit for rescue commander making up a correct disposal plan; This analysis can help to prevent the criminals from smuggling radioactive goods in customs and security check points and to distinguish the nature of abnormal radioactive alarm, which is a guarantee for national and social security.

The first step of most traditional RID methods is collecting the data of energy spectrum, and the second step is analysing these data by a certain algorithm[1-6]. It is a complex process and it takes a long time as this method is based on the statistical distribution energy of the γ-ray.

In 2009, J. V. Candy proposed a physics-based model for radionuclides identification by using sequential Bayesian approach[7], which can identify the type of radionuclides in a real-time way. This method made full use of the information of event mode sequence (EMS), including energy, time and emissivity, which greatly improved the speed of RID. But, using time information through statistical method directly will bring the error as the time interval will be influenced by the complete factors which cannot be confirmed in advance such as the activity of source, efficiency of the detection model and so on. And, if an invalid particle is judged as a valid particle, due to the intrinsic characteristics of EMS, the classification of the following particle will be disturbed.
This paper proposed a different algorithm with Candy, which abandons the use of EMS time information and establishes a new RID model at the cost of extending the number of iterations of the discriminant function appropriately. It has a lower false alarm rate and missed alarm rate, while the identification rate is still far faster than the traditional laboratory analysis method.

2. Theoretical descriptions

2.1. Radionuclide library and regions of interest
As the process of radionuclides identification always used in a specific environment which correspond to different groups of radionuclides, we can select different characteristic specific radionuclide libraries in advance according to different identification environments to improve the identifying efficiency and accuracy. For each characteristic radionuclide in specific radionuclide library, only one \( \gamma \)-ray will be used as research object whose emissivity is relatively large and energy is quite different from other radionuclides.

Since the \( \gamma \)-ray's full energy peak obeys Gaussian distribution [8], it is known from Gaussian function:

\[
p(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}
\]

where \( \mu \) is expectation of this distribution and \( \sigma \) is the variance. Therefore, if we define the region of interest(ROI) as the energy range centered on the characteristic \( \gamma \)-ray energy and having a width of \( 6\sigma \), the coverage of the peak area within the ROI may reach 99.76\%. According to the energy resolution of detector, such as 3.12\% for 0.662MeV \( \gamma \)-ray, we can calculate the ROI of the characteristic \( \gamma \)-ray of a radionuclide. For example, the ROI of \(^{137}\text{Cs}\) is \([0.6352, 0.6888]\). If we define the width of the ROI as \( 4\sigma \), the coverage of the peak area is up to 95.44\%. For example, the range of the ROI of \(^{137}\text{Cs}\) becomes \([0.6445, 0.6795]\).

2.2. Simulation of particle collection
The \( \gamma \)-rays emitted by radionuclides consist of a series of photons that carry different energies. During the radiation detection process, these photons are successively detected by the detector and converted into electronic signals. The resulting pulse sequence can be expressed as \( \{\varepsilon_i\} \).

According to the measured spectrum, the simulation is used to reproduce the pulse sequence formation process. In the simulation method to get the pulse sequence, we should first get measured spectrum. Then generate the random numbers. If

\[
\sum_{i=1}^{m-1} n_{i,i} < R < \sum_{i=1}^{m,n} n_{i,i}, \quad m=1, 2, \ldots, n
\]

where \( n_{i,i} \) is the counts of the spectrum in this channel and \( n_{0,0}=0 \), it means that the detector receives a particle of energy \( \varepsilon_m \).

2.3. Estimation of parameter
Each valid particle in the ROI may come from the counting of the full energy peak of the characteristic \( \gamma \)-ray, Compton scattering from other \( \gamma \)-rays, noise or background counts, and so on. If the radionuclide of interest is present, the ratio of the probability of a valid particle produced by the full energy peak of the corresponding characteristic \( \gamma \)-ray to the probability generated by the other effects should be estimated.

The counts generated by the full energy peak obey normal distribution \( x \sim N(\mu, \sigma^2) \) [8]. Taking the case that the width of the ROI is \( 6\sigma \), the formula will be deduced as follows. We suppose that the counting of background, noise and Compton scattering are uniformly distributed within the ROI,
which is \( r_U \sim U(\mu - 3\sigma, \mu + 3\sigma) \). If both the interest \( \gamma \)-ray and other effects exist, it can be obtained that the probability density function of the energy distribution of the valid particles in each ROI is:

\[
f(x) = \frac{A \times e^{-\frac{(x-\mu)^2}{2\sigma^2}} + mA}{\int_{-\infty}^{\infty} A \times e^{-\frac{(y-\mu)^2}{2\sigma^2}} dy + \int_{-\infty}^{\infty} mA dy} = \frac{e^{-\frac{(x-\mu)^2}{2\sigma^2}} + m}{\sqrt{2\pi}\sigma + 6m} \tag{4}
\]

where \( \mu \) is the energy of characteristic \( \gamma \)-ray, \( A \) is the probability of a valid particle generated by the full energy peak of the corresponding characteristic \( \gamma \)-ray, and \( m \) is the ratio of the probability generated by the other effects to the value of \( A \). The mathematical expectation of this distribution is \( EX = \mu \), and the variance is \( DX = \sigma^2 + \frac{12m\sigma^2}{\sqrt{2\pi}\sigma + 6m} \).

Using the information of valid particles that have been collected, we can estimate the value of the probability ratio

\[
\hat{m} = \frac{(s^2 - \sigma^2)\sqrt{2\pi}}{18\sigma^2 - 6s^2} \tag{5}
\]

where \( s^2 \) is the variance of the sample whose value can be calculated by

\[
s^2 = \frac{1}{n-1} \sum (\epsilon_i - \bar{\epsilon})^2 \tag{6}
\]

where \( \epsilon_i \) is the energy of the \( i \)th valid particle and \( \bar{\epsilon} \) represents the average value of energy for total valid particles.

So, according to the information of valid particles that have been collected, we can estimate the ratio of the probability of a valid particle generated by the full energy peak of the corresponding characteristic \( \gamma \)-ray to the probability generated by the other effects. And the smaller the number of valid particles used for parameter estimation, the larger the error. In order to avoid giving the identification result in the case of inaccurate parameter estimation, resulting in a higher error rate, a threshold \( n \) for specifying the minimum number of valid particles required for parameter estimation should be set.

According to the equation of variance \( DX \), it can be seen that \( DX \) increases monotonically with the increasing proportion of uniform distribution, while the value of \( DX \) is always within the interval \([\sigma^2, 3\sigma^2]\). Particle collection is a random process, so the sample variance \( s^2 \) may not always be in the above interval, so \( \hat{m} \) may be less than zero. Now we need to reset the value of \( \hat{m} \) based on two situations:

\[
\text{K0: } s^2 > 3\sigma^2, \\
\text{K1: } s^2 < \sigma^2
\]

When K0 occurs, it shows that the proportion of uniform distribution is far greater than the Gaussian distribution and we will draw a conclusion that this nuclide does not exist, while when K1 occurs, it indicates that the proportion of Gaussian distribution is far greater than the uniform distribution and we set \( \hat{m} = 0 \).

Meanwhile, the proportion of Gaussian distribution can be considered as low when \( \hat{m} \) is large. But the counts without full energy peak in the ROI do not necessarily follow the standard uniform distribution in the actual detection process, and there are some statistical fluctuations. In order to avoid false alarms caused by these statistical fluctuations, the nuclide will be considered absent when \( m > \zeta \) and \( \zeta \) is the upper bound of probability ratio.
2.4. Decision Function Updating and Threshold Selection

This nuclide identification process is carried out in real time, and each time a valid particle is recorded, it needs to be judged once to determine whether enough information has been obtained to determine whether the nuclide is present. Firstly we make the following assumptions:

H0: This radionuclide does not exist
H1: The radionuclide exists

Using the Bayesian criterion, the following decision function is introduced for the existence of the first radionuclide:

\[
L(n) = \frac{P(\varepsilon_n, H_1)}{P(\varepsilon_n, H_0)}
\]

(7)

where \( \varepsilon_n = \{e_1, e_2, \cdots, e_n\} \) is the energy sequence of the collected particles. The above equation can be equivalently expressed as follows:

\[
L(n) = \frac{P(e_n, \varepsilon_{n-1} \mid H_1)}{P(e_n, \varepsilon_{n-1} \mid H_0)}
\]

(8)

According to the Bayesian Probability criterion, we can get:

\[
L(n) = \frac{P(e_n, \varepsilon_{n-1} \mid H_1) \times P(\varepsilon_{n-1} \mid H_1)}{P(e_n, \varepsilon_{n-1} \mid H_0) \times P(\varepsilon_{n-1} \mid H_0)}
\]

(9)

It can be expressed in a sequential form:

\[
L(n) = L(n-1) \times \frac{f(e_n)}{g(e_n)}
\]

(10)

In the above formula, \( f(e_n) \) is the probability density function of particle energy distribution in the presence of the nuclide,

\[
f(e_n) = \frac{e^{-(e_n-\mu)^2/(2\sigma^2)} + m}{\sqrt{2\pi\sigma + 6\sigma m}}
\]

(11)

and \( g(e_n) \) is the probability density function of particle energy distribution in the absence of the nuclide,

\[
g(e_n) = \begin{cases} 
\frac{1}{6\sigma}, & \mu - 3\sigma < e_n < \mu + 3\sigma \\
0, & \text{others}
\end{cases}
\]

(12)

Each time a valid particle is reached, the decision-making function will be updated once and it will be judged according to the preset threshold whether identification result can be obtained or continue to be identified. We set the decision threshold based on Wald's sequential probability ratio theory [9]:

\[
P_1 = \frac{1 - \beta}{\alpha}, \quad P_2 = \frac{\beta}{1 - \alpha}
\]

(13)

where \( \alpha \) is the probability of the first type of error occurring, and \( \beta \) is the probability of the second type of error occurring. Compare the value of the value of decision function \( L(n) \) with \( P_1 \) and \( P_2 \):

If \( L(n) > P_1 \), it means the existence of the nuclide;

If \( P_2 < L(n) < P_1 \), it means that not enough information contained in the sample has been obtained to judge the type of radionuclide;

If \( L(n) < P_2 \), it can be determined that the nuclide was absent.
2.5. Algorithm flow

An effective way to identify radionuclides is to use the characteristic $\gamma$-rays emitted by them. The energy of $\gamma$-rays radiated by different radionuclides is different, which can be used as the “fingerprint” of radionuclides for radionuclide identification. Through this new algorithm, mining the information of pulse sequence can achieve a fast and accurate radionuclide identification process. The specific flow chart is shown in Figure 1.

![Flow chart of identification algorithm](image)

Figure 1. Flow chart of identification algorithm

The radionuclides identification process is always used in a specific environment, so at first we choose the appropriate radionuclide library according to the use of the environment to improve the identification efficiency. When a photon is collected by the detector and recorded, its energy information will be used to determine whether it is located in the ROI of a certain nuclide. If it belongs to, the energy information of the particle will be saved, otherwise it will be abandoned. When the number of stored particles is greater than the threshold value of the minimum number of particles required for parameter estimation $n$, conduct the parameter estimation by using the energy of the stored valid particles to get the ratio of the probability of a valid particle generated by the full energy peak of the corresponding characteristic $\gamma$-ray to the probability generated by the other effects and then updating the decision function. If it can reach the level of judgment, then output results, or wait for the arrival of next valid particle. When the number of valid particles exceeds the preset number for the first time, the decision function should be updated and discriminated by using the previously stored energy information.
3. Experimental

3.1. Experimental devices
This paper’s experiment is based on the BrilLanCe380 LaBr₃(Ce) detector, and the multichannel analyzer has 1024 channels. The gain is set to 0.75. The target high voltage is set to 500V while the actual high voltage is 495V. The point source is 25cm from the center of the detector surface. The energy resolution of this detector for 0.662MeV γ-ray of ¹³⁷Cs is 3.12%. The mixed energy spectrum of ⁶⁰Co and ¹³⁷Cs measured by this model is shown in Figure 2 where the 0.662MeV full energy peak of ¹³⁷Cs is located at the 334th channel and the 1.173MeV full energy peak of ⁶⁰Co is located at 592th channel.

![Figure 2. Mixed energy spectrum of ⁶⁰Co and ¹³⁷Cs measured by this model](image)

Using formula \( \text{FWHM} = a + b\sqrt{E} + cE^2 \), fit the energy broadening properties of the detector and then we can get the coefficients \( a = 0.002544 \), \( b = 0.01887 \), \( c = 0.6878 \).

3.2. The upper threshold of probability ratio
In order to avoid false alarms caused by statistical fluctuations of counts in the ROI as much as possible. If \( \zeta > m \), this nuclide can be considered absent. When the value of \( \zeta \) is larger, the missed alarm rate is smaller while the missed alarm rate is larger. When the value of \( \zeta \) is smaller, the false negative rate is larger while the false negative rate is smaller. In order to select the appropriate value of \( \zeta \), we take the value of \( \zeta \) equally spaced within a certain range, and then analyse different results experimentally.

3.3. The minimum number of valid particles needed for parameter estimation
If the minimum valid particle number \( n \) selected for parameter estimation is too small, the result of the parameter estimation will have a larger error. If \( n \) is too large, the waiting time of valid particles will be longer and the speed of radionuclides identification will be slower. Therefore, the optimal value of \( n \) should be selected through the experimental method.

3.4. The accuracy of no missed alarm
There are mainly five sources of counting contributions within a certain ROI: the counts of full energy peak of characteristic γ-ray; background counts; the counts of Compton effects from other energy characteristic γ-rays; the counts of full energy peak from other energy characteristic γ-rays; single or double escape peak counts from high energy γ-rays. Whether the characteristic γ-rays of other nuclides affect the accuracy of the identification when both interest nuclide and other nuclides both exist is a key factor in evaluating the effectiveness of the algorithm.
3.5. The accuracy of no false alarm

When the characteristic $\gamma$-ray of interest is absent, a large number of counts still exist inside the ROI, and the detector alarms caused by these particles are called false alarms. False alarm rate is an important indicator to measure the quality of an algorithm. The lower the false alarm rate, the better the algorithm performance.

4. Results and discussion

4.1. The width of the ROI is $6\sigma$

4.1.1. The upper threshold of probability ratio. In the experiment, the measured mixed energy spectrum of $^{137}$Cs and $^{60}$Co were used as the energy spectrum for the particle collection process. At this point, the characteristic peak of $^{137}$Cs at 0.662 MeV is located on the Compton plateau of $^{60}$Co, and is affected by the single escaping peak of 1.173 MeV characteristic $\gamma$-rays. Observe whether the accuracy of identification of $^{137}$Cs is affected by $^{60}$Co. Since the frequency is approximately equal to the probability when a large number of repeated experiments are conducted under the same conditions [10], it can be considered that the correct rate of no missed alarm is approximately equal to the accuracy of no missed alarm after 10,000 independent repeated trials. The relationship between the value of $\zeta$ and the accuracy of no missed alarm is shown in Table 1.

| $\zeta$ | 1   | 1.5 | 2   | 2.5 | 3   | 3.5 | 4   | 4.5 | 5   |
|---------|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| Accuracy of no missed alarm (%) | 95.43 | 98.27 | 99.16 | 99.22 | 99.34 | 99.54 | 99.63 | 99.68 | 99.72 |
| Average number of total particles | 389.8 | 394.9 | 398.3 | 400.3 | 400 | 400.3 | 400.6 | 401.2 | 400.5 |
| Average number of valid particles | 32.1 | 25.7 | 32.8 | 32.9 | 32.9 | 33 | 33 | 33.1 | 33 |

The measured $^{60}$Co energy spectrum is used as the energy spectrum for the particle collection process. Now observe whether the count of the contribution of both background and the single escaped peak of 1.173MeV characteristic $\gamma$-ray will cause false alarm of $^{137}$Cs or not. Repeat the test for 10000 times, and get the relationship between the value of $\zeta$ and the accuracy of no false alarm which is shown in Table 2.

| $\zeta$ | 1   | 1.5 | 2   | 2.5 | 3   | 3.5 | 4   | 4.5 | 5   |
|---------|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| Accuracy of no missed alarm (%) | 99.87 | 99.85 | 99.81 | 99.79 | 99.76 | 99.75 | 99.72 | 99.70 | 99.67 |
| Average number of total particles | 1064 | 1112.2 | 1175.3 | 1217.5 | 1317.3 | 1362.7 | 1441.6 | 1513.7 | 1548 |
| Average number of valid particles | 31.1 | 32.6 | 34.3 | 35.7 | 38.6 | 39.9 | 42.2 | 44.2 | 45.3 |

Through comparing the experimental results of different parameters, we set $\zeta = 4$ in order to achieve low false alarm rate and missed alarm rate at the same time, which means that this nuclide can be considered non-existent when $m > 4$.

4.1.2. The minimum number of valid particles needed for parameter estimation. The energy spectrum of the mixed radionuclides $^{137}$Cs and $^{60}$Co was used for particle collection process, and the accuracy of $^{137}$Cs identification was evaluated as $\zeta = 4$ and the value of $n$ was sampled in equal steps in a certain
range. For each value of $n$ repeated test 10000 times, we can get the relationship between the identification accuracy and the minimum number of valid particles needed to estimate the parameters, which is shown in Table 3.

| $n$  | Accuracy (%) | Average number of total particles | Average number of valid particles |
|------|--------------|-----------------------------------|----------------------------------|
| 5    | 72.6         | 166.5                             | 13.7                             |
| 10   | 88.5         | 227.3                             | 18.7                             |
| 15   | 95.1         | 273.5                             | 22.5                             |
| 20   | 97.9         | 312.7                             | 25.8                             |
| 25   | 98.9         | 353.4                             | 29.2                             |
| 30   | 99.6         | 399.8                             | 33                               |
| 35   | 99.8         | 447.4                             | 36.9                             |
| 40   | 99.9         | 501.6                             | 41.3                             |
| 45   | 99.9         | 555.7                             | 45.9                             |

Table 3. The relationship between $n$ and accuracy of identification

Balancing the accuracy and speed of identification, we can draw a conclusion that if $n$ is set to 30, the speed will be fast and the accuracy will also be high.

4.1.3. The accuracy of no missed alarm. The energy spectrum of the mixed radionuclides $^{137}$Cs and $^{60}$Co was used for the particle collection process. The threshold of the probability ratio $\zeta = 4$. The minimum number of valid particles used in the parameter estimation $n = 30$. Conduct the identification process within the ROI of $^{137}$Cs. The result is shown in Figure 3.

In the figure, each point represents an identification process, the abscissa represents the total number of particles collected in the identification process, and the ordinate represents the number of valid particles. Blue dots indicate the experiments that the identification is correct, while red asterisks indicate the missed ones. The correct rate is 99.5%. The average number of total collected particles is 400 and the average number of valid particles is 33. The algorithm has a low missed alarm rate.

When the energy calibration is not accurate or energy drift occurs, the measured energy will not match the actual energy, which also results in the missed alarm. Move the ROI of the certain radionuclides for $\rho$, then the relationship between the missed alarm rate and $\rho$ is shown in Table 4.

Table 4. The relationship between $n$ and accuracy of identification

| Center of ROI | Accuracy(%) | Average number of total particles | Average number of valid particles |
|---------------|-------------|-----------------------------------|----------------------------------|
| 0.662         | 99.65       | 400.6                             | 32.8                             |

Figure 3. $^{137}$Cs identification by $^{137}$Cs and $^{60}$Co mixed spectrum

Figure 4. $^{137}$Cs identification by $^{60}$Co spectrum
| Energy Deviation (keV) | ID Accuracy (%) | RID Accuracy (%) | Validation Rate (%) |
|------------------------|-----------------|-----------------|---------------------|
| 0.663                  | 99.54           | 403.0           | 33.0                |
| 0.664                  | 99.50           | 402.6           | 33.2                |
| 0.665                  | 99.47           | 410.2           | 33.8                |
| 0.666                  | 99.29           | 427.0           | 35.1                |
| 0.667                  | 98.99           | 447.9           | 36.8                |
| 0.668                  | 98.19           | 497.8           | 40.9                |
| 0.669                  | 96.93           | 553.9           | 45.2                |
| 0.67                   | 90.39           | 681.6           | 56.2                |
| 0.671                  | 82.81           | 793.9           | 64.3                |
| 0.672                  | 60.89           | 986.8           | 80.8                |
| 0.673                  | 39.81           | 982.3           | 78.6                |
| 0.674                  | 15.12           | 936.1           | 75.8                |

It can be found that when the energy deviation is less than 8keV, the accuracy of identification is still above 90%, but the accuracy of RID drops sharply with the distance of energy peak shifting. It is also reasonable and efficient since it greatly reduces the false alarm rate due to the γ-rays that are closer in energy to the gamma rays of interest. At the same time, the closer the correctness rate is to 50%, the more effective particles are needed to give the judgment result, which means that the more difficult the algorithm makes the "decision", the more valid particles are needed.

4.1.4 The accuracy of no false alarm. The measured $^{60}$Co energy spectrum is used as the energy spectrum for the particle collection process which is shown in Figure 4. The correct rate is 99.7%. The average number of collected particles is 1442 and the average number of valid particles is 42.2. It can be seen that it hard for Compton effect, escape peak effect, background and non-concerned nuclides to make false alarm.

4.2. The width of the ROI is 4σ

4.2.1. The optimal parameters. Similar to the case when the width of region of interest is 6σ, the measured mixed energy spectrum of $^{137}$Cs and $^{60}$Co are still used to analyze the presence or absence of $^{137}$Cs. Here we change both the upper threshold of probability ratio $\zeta$ and the minimum number of valid particles needed for parameter estimation $n$ at the same time, and then we can get the relationship between them and the identification results of no missed alarm, as shown in Figure 5.

![Figure 5. Relationship between the parameters and identification results of no missed alarm](image-url)
It can be seen that the highest false alarm rate can reach 94.5% when $\zeta = 1$, $n = 5$. And, the accuracy decreases with the increasing of the value of $n$. However, the trend of the average number of valid particles is opposite to the trend of the accuracy, and the number of valid particles required is at its minimum value when accuracy is the maximum.

Using the measured energy spectrum of the $^{60}$Co to analyze whether $^{137}$Cs is exist or not, we can get the relationship between the parameters and the identification results of no false alarm, as is shown in Figure 6.

![Figure 6. Relationship between the parameters and identification results of no false alarm](image)

It can be seen that when $\zeta = 6$, $n = 35$, the false alarm rate will reach its highest level, 98.88%. Accuracy decreases with increasing of the value of $n$. The accuracy changes little with the value of $n$, but is mainly affected by $\zeta$. The trend of the average number of valid particles is similar to the trend of accuracy.

In order to make radionuclides identification the best accuracy, we take both the false alarm and the missed alarm into consideration. Taking the average of the false alarm and the missed alarm, we can get the results of identification with the change of the parameters as shown in Figure 7.

![Figure 7. Relationship between parameters and comprehensive results](image)

It can be seen that when $\zeta = 1$, $n = 35$, the result reach the best with an accuracy of 92.6%, and the average number of valid particles required for judgment is 65.2. Compared with the former test, this result is poor. However, if the sample is more complex and has overlapping peaks, using a ROI with the width of $4\sigma$ may prevent the occurrence of the overlapping peak so the accuracy may be better.
4.2.2. False alarm caused by energy drift. For the case where the width of ROI is 4σ, considering the no false alarm caused by energy drift, the measured mixed energy spectrum of $^{137}$Cs and $^{60}$Co is still selected, and the presence or absence of $^{137}$Cs will be analyzed. Compare the test results with the test whose width of ROI is 6σ, which is shown in Figure 8.

![Figure 8. Relationship between the center of ROI and identification results](image)

(a) Average accuracy  
(b) Average number of valid particles  

When the energy center of the ROI are offset by the same distance, the accuracy is lower when the width of ROI is 4σ, and it varies rapidly with the energy shift. In the meantime, the average number of valid particles required for judgment in this case is relatively large.

5. Conclusions

Based on the sequential Bayesian method, this paper proposes a radionuclide identification algorithm whose speed is fast, only 30 to 50 valid particles will be collected to determine whether the interest nuclide exists. When the efficiency of full energy peak of detector is $10^{-2}$ and the photo fraction is 10%, the time required for identification is about 1s for $^{137}$Cs source with the activity of $10^4$ Bq, which makes significant progress in time consuming compared to most current RID methods. At the same time, the accuracy of false alarm and missed alarm for identifying single and mixed radionuclides is lower. We discussed the case of the width of ROI is 4σ and 6σ respectively, and the accuracy and efficiency are higher when the width of ROI is 6σ, but setting the ROI width to 4σ is beneficial to reduce the overlapping peaks. This paper is based on the LaBr$_3$(Ce) detector, and the accuracy will be higher if the higher energy resolution detector is selected such as HPGe detector.

However, this paper does not propose an effective model for identifying the closed peaks, only relying on detectors of high energy resolution which can narrow ROIs to avoid the overlapping peaks as much as possible, and it puts forward higher requirements for energy calibration. That all remains to be further studied.

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