Rapid radionuclide identification algorithm based on the discrete cosine transform and BP neural network

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ABSTRACT

Traditional radionuclide identification algorithm based on peak detection cannot recognize radioactive material in a short time. This study proposes a rapid radionuclide identification algorithm based on the discrete cosine transform and error back propagation neural network. Detection rate and accurate radionuclide identification distance were used to evaluate the proposed method. Experimental results show that the extracted feature vector of the spectrum is not influenced by time, activity, and distance. The proposed algorithm obtained better results in a relatively authentic environment, and it has the ability to predict the isotopic compositions of the mixed spectrum. The proposed method has a better identification performance for the spectrum of radionuclide masked by shielding material except the gamma rays emitted by related radionuclide are significantly shielded. It is also particularly recommended for the fast radionuclide identification of spectroscopic radiation portal monitors, radioisotope identification devices, and other radiation monitoring instruments.

1. Introduction

Radiation monitors are operated at checkpoints (e.g., borders and seaports) to detect and identify radioactive materials in a short time, as well as combat the illegal transportation of radionuclides (Bobin et al., 2016). However, no evident peaks in the gamma spectrum are observed during this short period. Difficulties can arise when the traditional method is used for fast radionuclide identification in this condition.

Artificial neural networks (ANNs) are mathematical models that emulate several of the observed properties of biological nervous systems and draw on the analogies of adaptive biological learning (Kangas et al., 2008). ANNs have been applied in gamma-ray spectrometry analysis (Medhat, 2012; Dragović and Onjia, 2005; Dragović et al., 2005; Dragović et al., 2006). Feature extraction is the kernel step of pattern recognition. Several previous studies have examined aspects of this topic in recent years. For example, Pilato et al. (1999) developed a new method for activity measurement by extracting the principal components of the gamma spectrum by singular value decomposition. However, the said researchers did not utilize it for radionuclide identification. Chen and Wei (2009) proposed a radionuclide identification method based on the Karhunen–Loeve transform (KLT) and neural network (NN), but the measuring time was approximately 1 min. Contrary to the traditional method, calibration, peak detection, and deconvolution are not required when utilizing NNs to analyze the gamma spectrum.

The present study proposes a novel rapid radionuclide identification algorithm based on the discrete cosine transform (DCT) and error back propagation (BP) NN. Experiments on different source types, time, activities, distances, number of radionuclide, and gamma-ray shielding were performed to verify the radionuclide identification performance of the proposed method.

2. Methods and experiments

The proposed algorithm is composed of background subtraction, feature extraction, and radionuclide identification. Fig. 1 shows the procedure of the proposed algorithm. First, the background and radionuclide spectra are both smoothed by wavelet decomposition. The subtraction spectrum is then obtained by subtracting the portion of the smoothed background spectrum according to the ratio of the radionuclide scan time to the background scan time. Second, the DCT is performed on the subtraction
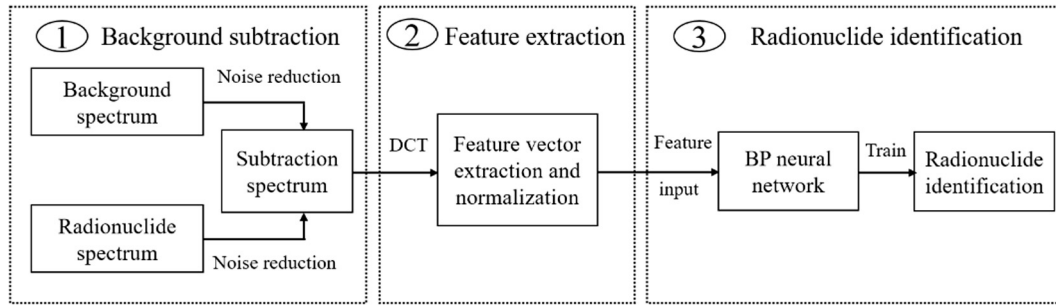
Fig. 1. Block diagram of the proposed algorithm.

spectrum to obtain the transformed spectrum. A certain number of transform coefficients is selected as the feature vector in the transformed spectrum. Finally, the normalized feature vector is inputted into the NN, and the trained NN is applied to predict the isotopic compositions of the spectrum.

2.1. Feature extraction

DCT is an orthogonal transformation method (Ahmed et al., 1974), and its transform kernel is a cosine function as shown in Eq. (1). It is often considered as the optimized transform of the speech and image signals, and its transform kernel is changeless, which only depends on the dimensions of data. The signal of transformed spectrum is mainly concentrated in the low frequency region, which provides a new way for feature extraction. DCT is a promising method for transforming the gamma spectrum. The spectrum can be seen as a vector y with the dimension of N, and then $y(x)$ ($x = 0, 1, 2, 3 \ldots N - 1$) is a form of discrete signal of the spectrum. Therefore, the spectrum can be expressed as Eq. (2) after DCT. Given that the signal of the $Y(u)$ spectrum is mainly concentrated in the low frequency region, more than 90% energy of the original spectrum can be reserved by selecting a small amount of transform coefficients in that region. The selected transform coefficients can be seen as spectrum features and are adopted as inputs for the NN. Thus,

$$t(x, u) = C(u)\sqrt{\frac{2}{N}}\cos\frac{(2x+1)u\pi}{2N} \quad C(u) = \begin{cases} \frac{1}{\sqrt{2}} & u = 0 \\ 1 & other \end{cases} \quad (1)$$

where u is an integer, that is, in the range of 0 to $N - 1$.

$$Y(u) = C(u)\sqrt{\frac{2}{N}}\sum_{x=0}^{N-1}y(x)\cos\frac{(2x+1)u\pi}{2N} \quad (u, x = 0, 1, 2 \ldots N - 1)$$

$$(2)$$

2.2. BPNN model

The BPNN is a multilayer feedforward NN that is trained by the BP algorithm. It is composed of input, hidden, and output layers (Yoshida et al., 2002). Each layer includes neurons that are connected to all the neurons of the succeeding layer. Weight, w_{ij}, exists for each connection between the two neurons, i and j. The neuron sums up all the signals it receives; each signal is multiplied by its associated weights on the connection, and the sum of the weights is processed with a certain activation function. This process describes the signal transmission in the NN. The initial weights of ANNs are often selected randomly by an algorithm, which can cause errors between the output and the target (actual). The BP algorithm works by minimizing the error through propagating it back into the network. The weights on each of the connections between the neurons are changed according to the error size. The

training is stopped when the root mean square error (RMSE) reaches an acceptable value. For machine learning, the key step is feature extraction, which can be completed by feature transform (e.g., KLT, DCT, singular value decomposition (SVD), fast fourier transform (FFT), etc.). BPNN may have better performance if we can extract the main feature of spectrum.

In the present study, 128 transform coefficients were selected as feature vectors of the spectrum; thus, the number of input neurons is 128. The number of hidden neurons is set at 8 according to the empirical Eq. (3). ^{238}Pu, ^{131}I, ^{60}Co, and ^{137}Cs are used to verify the proposed method; thus, the number of output neurons is 4. Each output indicates whether a radionuclide exists in the environment or not. Fig. 2 shows the BPNN model used.

$$k = \log_2 m \tag{3}$$

where m is the number of input neurons, and k is the number of hidden neurons.

2.3. Performance evaluation of the proposed method

In order to evaluate the proposed method, gamma ray spectrometry system which consists of $3'' \times 3''$ NaI (Tl) detector (ORTEC Inc.) coupled with a PC-based multichannel analyzer (MCA) (ORTEC Inc.) along with MAESTRO software installed in the PC was used, and MAESTRO 7.01 (ORTEC Inc.) software was used to obtain the spectra. The energy of this detector ranges from 30 keV to 3000 keV, and the resolution is approximately 7.7% (at 662 keV). The detector was installed at a fixed location, and the radionuclides were placed at points A, B,..., I in 20-cm intervals as shown in Fig. 3. Samples with different times, activities, and distances were obtained. The background spectrum without any source was collected for 300 s to generate the background template. Table 1 lists the radionuclides utilized in the experiment. They are labeled as Nucl-1, Nucl-2, Nucl-3, Nucl-4, Nucl-5, Nucl-6, Nucl-7, and Nucl-8 for convenience of description. The net count of each radionuclide measured at point A (Fig. 3) with detection time of 10 s was given, and the count of background with detection time of 10 s was also given. The dose rate of background without adding shielding apparatus was measured in the laboratory (about 0.1 μSv/h).

The detection rate was used to evaluate the identification performance of the proposed algorithm. The detection rate is defined by the ratio of the correctly identified data to the total amount of data as shown in Eq. (4) (Min et al., 2012):

$$Detection\ rate(\%) = \frac{TP + TN}{TP + TN + FP + FN} \times 100 \tag{4}$$

where *TP* is true positive, *TN* is true negative, *FP* is false positive, and *FN* is false negative.

The accurate radionuclide identification distance (ARID) of each radionuclide was calculated from the detection rate results with