Research on gamma spectrum semi-quantitative analysis based on convolutional neural network

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Abstract. In the field of practical application of nuclear technology, one of the vital steps is the interpretation of gamma energy spectrum, which can obtain the type and content of radionuclides and achieve further analysis. Convolutional neural network is one of the most basic and effective algorithm structures in deep learning because it has local receptive field, weight sharing and down-sampling structure, it solves the problem of parameter expansion caused by full connection and reduces the number of weights. That can be used to study the resolution of gamma-ray spectra of convolutional neural networks. This paper introduces the spectral forming principle of gamma spectra and the convolutional neural network, and uses the convolutional neural network to study the spectral decomposition of gamma spectra. In this paper, a multi-layer convolution neural network model is built based on C# software. The convolution neural network is applied to gamma-ray spectrum decomposition, and the U, Th, K nuclides are identified and semi-quantitatively calculated. By identifying and analyzing different energy spectrum data, it is shown that the modified model structure can be applied to the spectral decomposition of gamma spectrum.

1. Introduction

With the rapid development of computer technology, in order to make machine equipment have intelligent thinking ability when dealing with complex data, artificial neural network (ANN) is formed and has continuously developing over last three decades. Gamma spectrum analysis is regarded as a fast, reliable and non-destructive technology on determining the type and intensity of radionuclides [1]. The concepts of convolution neural network (CNN) and convolution kernel came into being. At present, the neural network has developed to a certain stage. There are not only types in structure, but also breakthroughs in algorithm. Therefore, the application of convolutional neural network in gamma spectrum is feasible.

For nuclear science and technology, it is also natural to apply ANN to gamma-ray spectroscopy. As early as last century, scholars began to study the use of neural networks for gamma-ray spectrum analysis. Olmos put forward the neural network in 1992 and Vigneron proposed in 1996 to use the neural network to carry out statistical modeling in gamma-ray spectrum analysis [2]. Because the neural network has the functions of non-linear mapping, fast parallel distribution processing and recognition of spectral features for energy spectrum analysis [3], the results of nuclide recognition can
be obtained quickly and accurately in the analysis and processing of gamma spectrum. In recent years, the research of using neural networks to solve gamma-ray spectra has also begun to increase gradually in China. Jianwen Huo used probabilistic neural networks for rapid identification of radionuclides in 2005 [4]. Chongjie Wang used RBF artificial neural networks to analyze gamma-ray spectra in 2016 [5]. Jianping He used the neural network model to train the fast nuclide recognition based on Walsh-Hadamard transform and stack self-coding published in 2017 [6].

The application of convolution neural network in gamma-ray spectrum decomposition analysis is essentially to identify the spectrum image, so as to find the characteristic peaks of the spectrum, and ultimately get the spectrum information through analysis. The decomposition gamma spectrum of convolution neural network is different from that of traditional gamma spectrum. It extracts features directly from the spectrum data, and then obtains the categories and contents of elements through appropriate weights.

This paper mainly studies the qualitative evaluation of K, U and Th elements by using multi-layer convolution method based on C# platform. C# platform can greatly reduce the number of parameters of multi-layer convolutional neural network and locally optimize the structure of the neural network.

2. Material and method

2.1. Convolution principle

Convolution is divided into two categories, one is discrete convolution, referred to as convolution sum, such as formula 1; the other is continuous convolution, referred to as convolution integral, such as formula 2.

\[
 f[x]*g[x] = \sum_{k=-\infty}^{\infty} f[k]g[x-k] \tag{1}
\]

\[
 f(x)*g(x) = \int_{-\infty}^{\infty} f(k)g(x-k)dk \tag{2}
\]

Where, \( x = K + (x-k) \), this means that every input data has a corresponding weight [7]. All the methods adopted in this paper are based on discrete convolution, and the matrix is convoluted by discrete convolution.

2.2. Principle of Convolutional Neural Network

CNN can automatically learn training weights in supervised mode, and constantly extract features from sample data. Traditional pattern recognition is generally not very effective and convolutional neural network has good effect on image recognition. The structure of convolutional neural network mainly includes sparse connection and value sharing. It has three forms of constraints: feature extraction, feature mapping and sub-sampling.

2.3. Convolutional neural network structure

Convolutional neural network is mainly composed of convolution layer, sub-sampling layer and full connection layer. After convolution operation, the features will be mapped to the next layer, and then the data features will be extracted by using the layer. The convolution layer and the sampling layer alternately form the feature extraction layer of an input layer, and then the data after feature extraction is used as the input layer to continue feature extraction. Finally, the entire connection is carried out to classify the output layer and obtain the output result [8]. Figure 1 shows the technical route in details.
3. Results and discussion

3.1. Experimental Selection of CNN Structural Quantity Method

Through theoretical study and analysis, the number of convolution cores selected is 6. The convolution layer and the pooling layer have two layers respectively. Finally, there is one layer of full connection layer. Firstly, 1024-channel gamma-ray spectroscopy data are input to form a 32*32 two-dimensional matrix. The energy spectrum data are arranged horizontally into a two-dimensional matrix, as shown in Figure 2. The positions of the energy peaks of U, Th and K nuclides are generally different, and the positions of all energy peaks are basically kept within a range. Therefore, the positions of nuclide corresponding matrices of U, Th and K are basically unchanged in the 32*32 two-dimensional matrices. The dimension matrix is regarded as a pixel image, and the feature pixels of U, Th and K nuclides in the image are recognized by grasping the feature information of the image, so as to realize the possible spectral recognition.

![Figure 2. The arrangement of the input energy spectrum data to form a matrix](image-url)
The first convolution layer is to convolute the input layer data according to different convolution kernels. The convolution core moves in the same way as the two-dimensional matrix of 32*32 composed of energy spectrum data, as shown in Figure 2. The first pooling layer is to pool six feature mapping matrices obtained from the first convolution layer and get six 14*14 feature extraction matrices. In this experiment, the maximum pooling method is used to select the maximum value in the 2*2 region of each feature mapping matrix and each maximum value is taken as a value in the feature extraction matrix. The pooling method is the same as the two-dimensional matrix of energy spectrum data, which not only reduces the dimension, but also makes the feature data more prominent and concentrated.

Because a "convolution-pooling" process can not accurately extract features, we need to construct another layer and finally get six 5*5 feature extraction matrices. After full connection, the mapping feature real numbers are converted to be between [0,1]. The final function value can be used to judge whether there are U, Th and K nuclides in gamma spectrum and the content of U, Th and K nuclides can be calculated according to the output results.

3.2. Evaluation of experimental results
The energy spectrum data used in this experiment are obtained from a geological exploration survey and detected by gamma ray spectrometer. Among them, the range of K-peak is 458-470, U-peak is 555-564, and U-peak is 826-858. In this paper, 80 sets of energy spectrum data are obtained. Fifty-six of them are used as training samples according to the proportion of 7:3. The remaining 24 sets of energy spectrum data are used as experimental group to test the effect of neural network model.

The two-dimensional matrix of the spectral line yields the following initial bottom convolution data. If its two-dimensional matrix is represented by gray scale graph, figure 3 can be obtained.

![Figure 3. Color scale image of energy spectrum data](image)

The initial convolution graph is input into the neural network model, and a series of operations such as convolution, pooling and full connection are carried out. The output result is 0.5473.

In the experiment, a group of gamma-ray spectra data was used as standard reference spectra. It is known that there are U, Th and K nuclides in the gamma-ray spectra, and the contents are shown in Table 1.
Table 1. K, U, Th Contents in Standard Energy Spectrum

| K content /% | U content /ppm | Th content /ppm |
|--------------|----------------|-----------------|
| 2.76         | 2.21           | 9.4             |

The standard gamma-ray spectrum data is input into the convolutional neural network model built on C# platform and the output is 0.5477. Then other energy spectrum data are input into the program in order to make the result more accurate (see figure 4).

Figure 4. Sample data output in convolution neural network

After recognition by the convolution neural network program, it can be found that U, Th, K nuclides exist in each group from the chart. Compared with the actual results, the results are correct.

Table 2. Relevant data of K measured by experiment

| Serial number | K content (μg · g⁻¹) | Maximum counting of experimental data | Maximum count for each set of data | K peak channel | K peak count |
|---------------|----------------------|--------------------------------------|-----------------------------------|---------------|-------------|
| 1             | 2.62                 | 1051                                 | 907                               | 458–470       | 339         |
| 2             | 2.53                 | 1051                                 | 925                               | 458–470       | 357         |
| 3             | 2.64                 | 1051                                 | 883                               | 458–470       | 342         |
| 4             | 2.69                 | 1051                                 | 1051                              | 458–470       | 328         |
| 5             | 2.67                 | 1051                                 | 999                               | 458–470       | 350         |
| 6             | 2.67                 | 1051                                 | 973                               | 458–470       | 348         |
| 7             | 2.48                 | 1051                                 | 986                               | 458–470       | 327         |
| 8             | 2.65                 | 1051                                 | 980                               | 458–470       | 331         |
| 9             | 2.54                 | 1051                                 | 987                               | 458–470       | 334         |
| 10            | 2.63                 | 1051                                 | 1005                              | 458–470       | 332         |
| 11            | 2.72                 | 1051                                 | 990                               | 458–470       | 372         |
| 12            | 2.73                 | 1051                                 | 946                               | 458–470       | 324         |
| 13            | 2.04                 | 1051                                 | 976                               | 458–470       | 316         |
| 14            | 2.32                 | 1051                                 | 981                               | 458–470       | 345         |
Table 2, cont

| No. | K content/\% | Energy (keV) | Gamma-ray Spectrum K content | Predicted value range |
|-----|--------------|--------------|-----------------------------|----------------------|
| 15  | 2.01         | 1051         | 989                         | 458–470              | 318                   |
| 16  | 1.94         | 1051         | 725                         | 458–470              | 278                   |
| 17  | 1.92         | 1051         | 752                         | 458–470              | 276                   |
| 18  | 2.6          | 1051         | 776                         | 458–470              | 295                   |
| 19  | 2.73         | 1051         | 871                         | 458–470              | 270                   |
| 20  | 2.54         | 1051         | 820                         | 458–470              | 275                   |
| 21  | 2.08         | 1051         | 751                         | 458–470              | 240                   |
| 22  | 1.89         | 1051         | 848                         | 458–470              | 255                   |
| 23  | 2.38         | 1051         | 784                         | 458–470              | 320                   |
| 24  | 2.51         | 1051         | 750                         | 458–470              | 298                   |

The experiment was quantitatively calculated based on standard energy spectrum. The experimental group selected K content for quantitative analysis (see table 2). According to the normalized results and standard gamma-ray spectrum K content to predict the experimental group of gamma-ray spectrum K content (see figure 5).

Relative errors are calculated according to the predicted and real values of potassium content in experimental samples. Compared with the actual results, the absolute error of gamma-ray spectrum K content calculated by convolution neural network model is not large. The minimum and maximum relative errors are 0.82 and 44.19 respectively. By calculating the relative error with 5% of the initial value, the qualified rate is 37.5%. If the relative error is calculated by 10%, the qualified rate is 62.5%. It basically meets the expected requirements.
4. Conclusion
This design chooses convolution neural network as the experimental model and optimizes the model of convolution neural network. Finally, the convolution neural network model is applied to the gamma-ray spectrum decomposition to identify K, U, Th nuclides and calculate the content. The feasibility of convolution neural network model is proved by comparing experiment with practice. However, the comparison results show that there are some deviations between the experimental results and the standard, which indicates that there is still room for further optimization in the model structure and parameter selection of convolutional neural network. The application of convolution neural network in gamma spectrum resolution is effective and has great potential, which can be further studied.

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References
[1] Fei Li, Zhixing Gu, Liangquan Ge, Hui Li, Xinyu Tang, Xinle Lang, Bo Hu. Review of recent gamma spectrum unfolding algorithms and their application. Results in Physics. 2019,13:102211.
[2] V. Vigneron, J. Morelb, M.C. Lkpyb, J.M. Martineza. Statistical modelling of neural networks in y-spectrometry. Nuclear Instruments and Methods in Physics Research. 1996,369:642-647.
[3] Donsheng Shi. Application of Particle Swarm Optimization in Recognition of Gamma Spectrum by Neural Network. Nuclear Technology. 2007, (7): 615-618.
[4] Chongjie Wang. Gamma Spectrum Analysis Based on RBF Artificial Neural Network. Nuclear Electronics & Detection Technology. 2016, (1): 56-59.
[5] Jianwen Huo. Research on Rapid Recognition of Radionuclides Based on Probabilistic Neural Network. Nuclear Electronics & Detection Technology. 2015, (3): 253-258.
[6] Jianping He. Fast Nuclide Recognition Based on Walsh-Hadamard Transform and Stack Self-Coding. Nuclear Electronics & Detection Technology. 2017, (8): 834-840.
[7] Jian CHENG,Pei-song WANG,Gang LI,Qing-hao HU,Han-qing LU. Recent advances in efficient computation of deep convolutional neural networks. Frontiers of Information Technology & Electronic Engineering. 2018, 19(01):64-77.
[8] Dan Li. An Improved Convolutional Neural Network Based on Lenet-5. Computer Age. 2016(08):4-6.