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Recognition of Fission Signals Based on Wavelet Analysis and Neural Network

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Abstract

Because of the particularity of the uranium components, the nondestructive measuring technique is needed to detect the radioactivity of the component in certain container and identify their property to recognize all kinds of uranium components. This paper establishes a set of samples with the same shape, different weight and abundance of uranium by simulation. Secondly the cross-correlation function of time-relation signal between the source detector and the detector could be calculated. Lastly the result of cross-correlation functions is through micro-wavelet analysis to obtain feature vector which is related to the quality and abundance property of target uranium components. This vector is used to train neural network and help to identify the quality and abundance of unknown uranium components.

Keywords: *micro-wavelet analysis, neural network, uranium component.*

1. Introduction

The detection of uranium components is an aporia in the nuclear disarmament.Nuclear components include uranium components and plutonium components.Both the intensity of spontaneous fission of neutrons and gamma-ray in metal uranium are weak, and with strongly self-shielding effect. So it is difficult to detect metal uranium through passive detecting methods [1-3]. Some researchs based on active inducing method, which makes the exogenous neutrons enter uranium components and produce scattering, absorbing and induce fissions by active inducing uranium components [4], indicate that the neurons produced by induced fissions are scattered or cause next generation induced fissions, multi-generation fissions could form a fission chain, and the neutrons on the same chain are related [5, 6]. If the relation-ship could be sampled , described, and regular, the recognition of nuclear components could be given through analysis the relationship between the characteristic signal of components and their features.

Beacuse of the experimental data from active inducing method are disperse, varied and massive. The relation-ship is very hard to extracted and described. Traditonal mathmatics theory is hardly to work out the relation-ship function or describe model for recognition of uranium components in short time and effective [1, 6]. This paper devotes works to built wavelet packet analysis method to extract the feature signals of uranium components and use a B-P neural network to identify the property of uranium components. The micro-wavelet analysis is very efficient to deal with the disperse signals and neural network is helpful to build describe model for varied and less-related data.

2. Research method

The measurement model is as Figure 1 by using active method to detect uranium components. In Figure 1, the time detector 1 is used to capture the signals such as fission fragments, alpha particles and etc, which all induced by neutron source. The detector 2 and 3 are used to obtain the neutrons and γ rays which induced by neutron source from the uranium components. The neutron source is mainly made of ^{252}Cf, which generates 4 neutrons and 6γphotons in every spontaneous fission. The neutrons and γ rays from spontaneous fission of neutron source break into the uranium components and produce chain reaction. The detector 1, 2, 3 would capture the time related impulse signal of new neutrons produced by fission of

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uranium components. Uranium components are the target of fission signals feature analysis and recognition based on BP neural network in this paper.

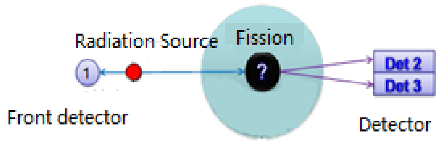

Figure 1. Measurement model sketch map of active detecting uranium components

2.1. The Simulation of the Fission Signals by Active Inducing Uranium Components

To protect the privacy of source data, all data of the active detect experiment in this paper are changed and added the noise-part on time-line. According to the active fission theory, 4 kinds of cylinder sample with different weight are selected as the experiment targets, and the weight such as 20kg, 16kg, 12kg & 10kg. The 4 cylinder samples are with different height and radius. Each sample has 4 types concentration of U235(0.2wt%, 36.0wt%, 50.0wt%, 93.15wt%). Thus the cross-correlation function should be calculated toward the 16 group data.

Figure 2 shows the correlation-functions of four uranium components samples with fixed mass of 20kg and different densities--- 0.2wt%, 36.0wt%, 50.0wt%, 93.15wt%, Figure 3 shows the correlation-functions of four samples with fixed density of 36.0wt% and different weight--- 20kg, 16kg, 12kg and10kg. In Figure 2, the correlation-functions curve of fixed weight (20kg) and different densities (respectively 0.2wt%, 36.0wt%, 50.0wt% and 93.15wt%) consists of two peaks. Moreover, four curves from 0ns to 20ns have no obvious difference, and from 20ns to 60ns the curves split. The reason is that neutrons in this phase was generated mainly by fission of uranium components, and the signals of this phase are related to density of components. The features of signals also are affected by time. It is obvious that in Figure 3 the first peak of correlation-functions curve is related to the weight of components, and correlation-functions from 20ns to 60ns are also related to the weight of components and affected by time. So by analyzing the correlation-functions of uranium components, the features reflected the weight and abundance of target could be got [7, 8].

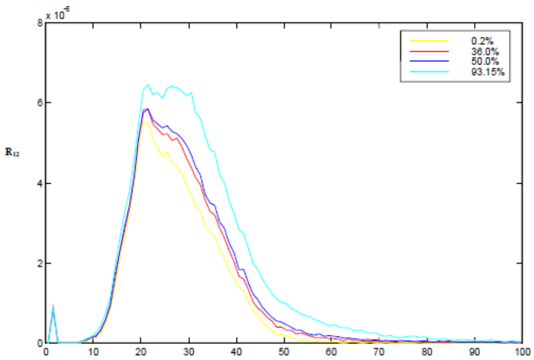

Figure 2. Source-detector cross-correlation functions for uranium components of different abundances and fixed mass (20kg)

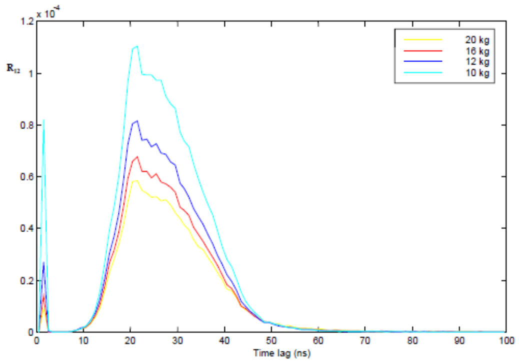

Figure 3. Source-detector cross-correlation functions for uranium components of different masses and fixed density (36%wt U-235)

2.2. Extracts the Features of Fission Signals Based on Wavelet Packet Analysis Method

Wavelet transform is a processing and analyzing method for signals of multi-scales with good time-frequency localized features [9-11], so it is very suitable for processing nuclear signals of fission neutrons with transient and time-varying characteristics. Usually, wavelet decomposition only decomposes low-frequency coefficients into two parts, while wavelet packet analysis further decomposes frequency of wavelet space based on binary system manner which makes wavelet packet overcome the problem of high time resolution but low frequency resolution, thus providing more precision analysis method for signals. Figure 4 is the three-level wavelet packet decomposition structure diagram.

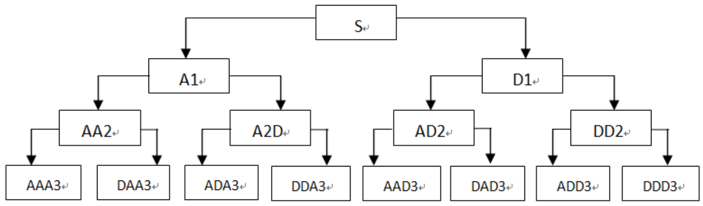

Figure 4. Three-level wavelet packet decomposition structure diagram

As it could be seen from the wavelet packet decomposition structure diagram, wavelet packet decomposition compartmentalizes frequency-band to multi-levels and further decomposes high-frequency which is no subsection in wavelet decomposition. Wavelet packet decomposition could self-adapting choose homologous frequency-bandin accordance with the feature of analyzed signals and make it match with frequency spectrum of the signals to improve the resolutions of time domain and frequency domain [12, 15].

2.3. Feature Extraction Steps Based on Wavelet Packet Analysis

After going through detected system, the output signalsof different components differ in energy space distribution, in other words, the transformation of output energy includes the feature information of the components. Therefore, extracting the features of components from signals energy in every subspace distribution, namely using wavelet packet transformation to analyze signals in different frequency-band of multi-level decomposition could make unobvious signals frequency features visible with marked energy-varying form in many subspaces of different resolutions. The following is basic steps of this method [13-14], [16].

Step1: Decompose sampling signals based on wavelet packet decomposition. The decomposition layersare in line with the complexity degree of signals. Extract signal features of every frequency elements in the last layer. It adopts three-layer decompositionin this paper, and extracts frequency elementsof the third layer respectively from low-frequency to high-frequency. Figure 4 is the decomposition structure: in the figure, (i, j) represents the j-th node of the i-th layer where$\boldsymbol{i} = \mathbf{0}, \mathbf{1}, \mathbf{2}, \mathbf{3}. \boldsymbol{j} = \mathbf{0}, \mathbf{1}, \mathbf{2}, \mathbf{3}, \mathbf{4}, \mathbf{5}, \mathbf{6}, \mathbf{7}$, and $\boldsymbol{x_{ij}}$ represents the decomposition coefficient at the j-th node of the i-th layer.

Step2: Restructuring wavelet packet decomposes coefficient and extract signal$\boldsymbol{S_{ij}}$from every frequency band. $\boldsymbol{S_{ij}}$ represents restructured signal of$\boldsymbol{x_{ij}}$In this paper, only nodes of the third layer are analyzed, so the total signal S could be represented by formula (1):

$$S = S_{30} + S_{31} + S_{32} + S_{33} + S_{34} + S_{35} + S_{36} + S_{37} \quad (1)$$

Step3: Compute the total energy of each frequency band. Suppose that $E_{ij}$is the energy of restructured signals$\boldsymbol{S_{ij}}$, then:

$$E_{ij} = \int |S_{ij}(t)|^2 \, dt = \sum_{k=1}^{n} |x_{ij}(k)|^2 \quad (2)$$

In formula (2), $x_{ij}(k)$ represents the k-th discrete point amplitude of the restructured signal at the i-th layer and the th node, and n represents the number of discrete points.

Step4: Structure feature vector.

$$T = [E_{i0}, E_{i1}, \cdots, E_{i(2^i-1)}] \quad (3)$$

When energy is too powerful, the value of $E_{i(2^i-1)}$ gets bigger too, which will bring inconvenience for data analysis, so it is needed to uniformize energy. The total energy of signal E is :

$$E=\sum_{j=0}^{2^i-1}E_{ij} \tag{4}$$

$$T^{'}=[E_{i0},E_{i1},\cdots,E_{i(2^i-1)}]/E \tag{5}$$

$T^{'}$ is the vectorafter uniformization

As it couldbe seen from formula (4), energy distance M_{ij} not only counts in energy size but also the energy distribution status on time axes---representing by parameter t in formula. In this case, compared with formula (1), it could better post distribution feature of energy, thus is help to extract components attributions features. So formula (5) could be rewritten as formula (6):

$$T'=[M_{i0},M_{i1},\ldots,M_{i(2^i-1)}]/\sum_{j=1}^{(2^i-1)}M_{ij} \tag{6}$$

2.4. Feature Extraction of Uranium Components Fission Signals Based on Wavelet Packet Decomposition

In the process of active inducing uranium components fission, fission signals reflect abundant information of uranium components attributions. So it is feasible to get attributions information of uranium components through analyzing fission signals. But when fission signals are stochastic and non-balance, it is difficult to observe inner fission rules of uranium components from external changes. In order to find its intrinsic rules, it needs using modern technology to process primal signals. Therefore, how to extract attribution feature information from fission signals is the key of successful recognition of attributions in the attributions recognizing process. The extracted features should be sufficientsensitive to different attributions, which requires the feature extraction method could extract attribution information that hides in signals. Wavelet transformation is fit for feature extraction of non-balance signals. At present, wavelet analysis has been applied to feature extractions of many signals and achieved good results.

In the active inducing uranium components fission, its energy space distribution of output signals includes abundant attribution feature information. Therefore, it makes unobvious signals frequency features to appear with marked energy-varying form in many subspaces of different resolutions by extracting attribution features from signals energy in every subspace distribution, namely analyzing signals of different frequency band after multi-layer decomposition with wavelet packet transformation, and then extract feature information which reflects uranium components attributions.

Following the analysis steps inIII, processing source-detector’s cross-correlation functions of four components samples with fixed mass (20kg) and different density (respectively 0.2wt%, 36.0wt%, 50.0wt% and 93.15wt%) get their energy distance distribution diagram as Figure 5(a) and (b). Processing source-detector's cross-correlation functions of four components samples with different masses (respectively 20kg, 16kg, 12kg and 10kg) and fixed density (36.0wt%) get their energy distance distribution diagram as Figure 6(a) and (b).

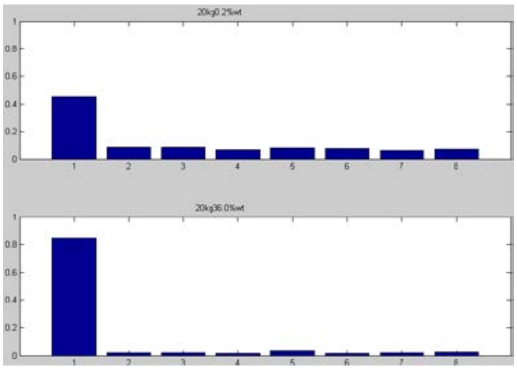

Figure 5(a). Energy distance distribution diagram of uranium components with fixed mass (20kg) and different densities (respective 0.2wt%235U and 36.0wt%235U)

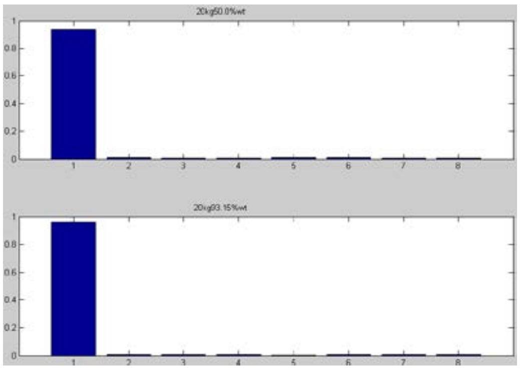

Figure 5(b). Energy distance distribution diagram for uranium components with fixed mass (20kg) and different densities (respective 50.0wt%235U and 93.15wt%235U)

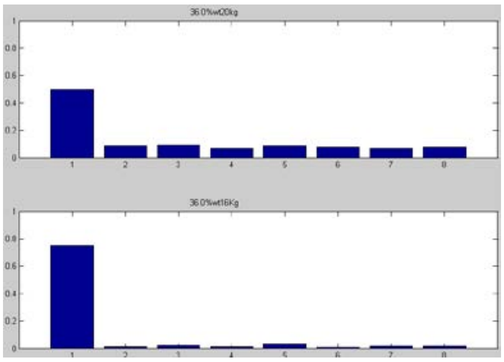

Figure 6(a). Energy distance distribution diagram for uranium components with different masses (respective 20kg and16kg) and fixed density (36.0wt %)

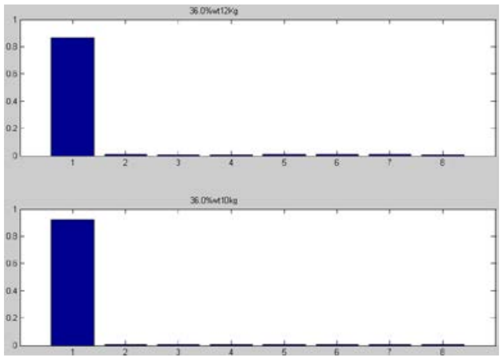

Figure 6(b). Energy distance distribution diagram for uranium components with different masses (respective 12kg and10kg) and fixed density (36.0wt %)

Te1, Te2, Te3 and Te4 respectively represent energy distance feature vectors of uranium components of different densities (respectively 0.2wt%, 36.0wt%,50.0wt% and 93.15wt%235U) and fixedmass (20kg). Tm1、Tm2、Tm3 and Tm4 respectively represent energy distance feature vectors of uranium components of different masses (respectively 20kg, 16kg, 12kg and10kg) and fixed densities (36.0wt%235U).

2.5. Identifies Masses and Abundance of Uranium Components Based on BP Neural Network

In accordance with topological structure and operation mode of network, neural network models include feed-forward multi-layer network model, feedback recursion network model, random network model and etc. The mature model in pattern recognition is error Back Propagation (BP) model, which is one of feed-forward multi-layer network models. BP network has not only input and output nodes, but also makes one layer or many layers with connotative nodes. For input information, BP propagates to connotative layers nodes at first, and then propagates to output nodes through output information of connotative nodes, and finally gives output results. Networklearning process consists of two parts---forward propagation and back propagation.

Masses of sample cylindrical componentsin this paper are respective 20kg, 16kg, 12kg and 10kg, and the densities of each different mass component are respective 0.2wt%, 36.0wt%, 50.0wt% and 93.15wt%, which amount to 16 components samples. It includes two simulations:

the fixed mass with different densities and the different masses with fixed density. It firstly processes and analyzes relevant simulation data, and then processes with wavelet packet decomposition, and finally gets their energy distance feature vectors which are taken as learning samples of BP neural network. Target output T1[2×16] and T2[2×16] represent the masses and U235abundances of every sample.

$$T1=\begin{bmatrix} 20\ 20\ 20\ 20\ 16\ 16\ 16\ 16\ 12\ 12\ 12\ 12\ 10\ 10\ 10\ 10; \\ 0.2\ 36\ 50\ 93.15\ 0.2\ 36\ 50\ 93.15\ 0.2\ 36\ 50\ 93.15\ 0.2\ 36\ 50\ 93.15 \end{bmatrix}$$

$$T2=\begin{bmatrix} 20\ 16\ 12\ 10\ 20\ 16\ 12\ 10\ 20\ 16\ 12\ 10\ 20\ 16\ 12\ 10; \\ 0.2\ 0.2\ 0.2\ 0.2\ 36\ 36\ 36\ 36\ 50\ 50\ 50\ 50\ 93.15\ 93.15\ 93.15\ 93.15 \end{bmatrix}$$

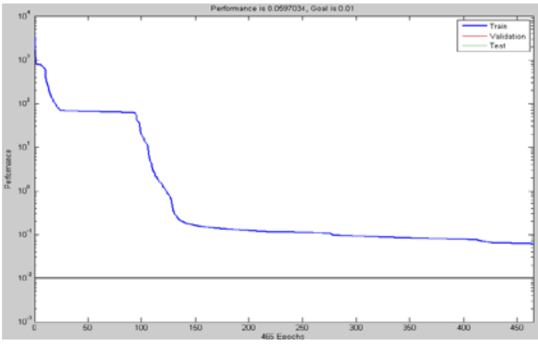

Figure 7(a). Training curve of fixed mass components

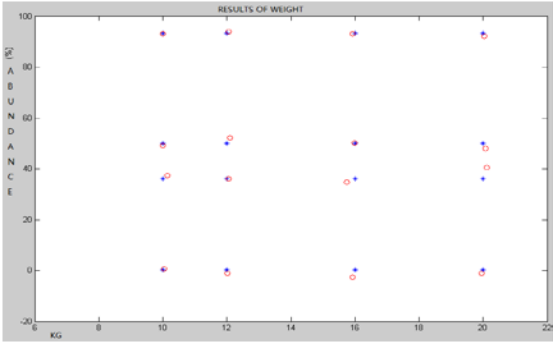

Figure 7(b). Recognition results of fixed mass components

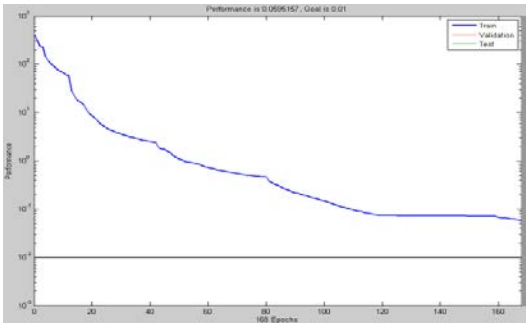

Figure 8(a). Training curve of fixed abundance components

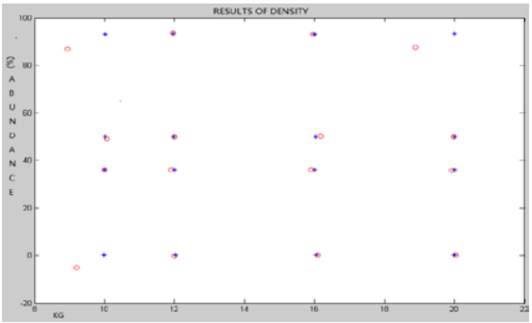

Figure 8(b). Recognition results of fixed abundance components

According to Kolmogorov theorem of neural network theory, 3-layer BP network with full learning model couldapproximate to any function. This paper chooses 3-layer BP network, and name a BP network with single hidden layer. Input layer nodes of the network are determined by the input vector dimension which is 8 here, so the input layer nodes are 8 too. Output layer nodes are determined by the output vector dimension which is 2 here. There is no theoretical guidance in all BP network about the selection of hidden nodes. Excessive network nodes would expand the training time and diminish generalization capacity as well as the predictive ability of the network, while insufficient network nodes could note reflect the relationship between the follow-up value and the precursor value, which leadsinsufficiency of modeling. The number of hidden layer node issetat amount of10 in this paper after repeated training, and an8-10-2 BP neural network is designed from hidden layers. The BP neural network is programmed and taken intest running by the MATLAB R2010a. The neural network designed in this paper to train signal energy distance vector of four uranium components with fixed mass and different densities, of which training process and results are represented as Figure 7(a) and (b), and then to train signals energy distance vector of four uranium components with different masses and fixed densities, which training process and results are represented as Figure 8(a) and (b).

3.Results and Analysis

3.1. The analysis of BP

Due to particularity, sensitivity and complexity of the research objects, this paper chooses a training method combining really measured data with some noise and simulation data. Paper then chooses one group of simulation data with noise to test the network. The test result of masses and abundances are as Figure 7(b) and Figure 8(b). From the analysis results in Table 1 and Table 2, it indicates that predicted value based on BP neural network designed in this paper is closer to the true value. Average relative error in Table 1 is only 0.48%, and 1.96% in Table 2. As for the density prediction, the average relative error is respectively to 27.49% and 25.35%. It also indicates from the table that for high abundance uranium, the predicted value of its abundance is close to the true value, but it is not fit for the low abundance uranium. The reason is that only the data of simulated fission for uranium components is used for BP but lack of reality data to adjust. If enough sample of low density could be used in BP, the method of decreasing the noise and increasing the accuracy for low abundance uranium would be developed.

Table 1. Prediction results for uranium components of different abundances and fixed masses taking energydistance of detected signals as feature vectors

	Kg/%wt Real	Kg/%wt BP	Kg/%wt Error
1	20/0.2	19.95/-1.20	0.25/116.6
2	20/36.0	20.12/40.42	0.61/10.94
3	20/50.0	20.07/48.03	0.36/4.11
4	20/93.15	20.04/92.19	0.20/1.04
5	16/0.2	15.93/-2.72	0.44/107.3
6	16/36.0	15.74/34.70	1.66/3.75
7	16/50.0	15.98/50.07	0.12/0.15
8	16/93.15	15.93/93.13	0.43/0.02

Table 2. Prediction results for uranium components of different masses and fixed abundances taking energy distance of detected signals as feature vectors

	%wt/Kg Real	%wt/Kg BP	Kg/%wt Error
1	0.2/20	0.17/20.03	0.15/20.91
2	0.2/16	0.19/16.10	0.63/8.11
3	0.2/12	-0.13/12.00	0.02/256.8
4	0.2/10	-5.00/9.20	8.65/104.0
5	36.0/20	35.88/19.93	0.35/0.33
6	36.0/16	35.96/15.91	0.54/0.11
7	36.0/12	36.04/11.91	0.77/0.11
8	36.0/10	36.00/10.00	0.00/0.00

3.2. The Comparison

Table 3 is a comparison between traditional experimental average-value (AVE) method BP method. BP method is faster and more effective. If put the consideration on the costs to get the basic data from the acitve-induce system(20G points would be recorded in one active-induce), BP method is more valuable and saves a lot of money and time.

Table 3. The comparsion of AVE and BP

	Sample points(G)	Time(s)	Accuracy (%)	Error (%)
BP	20G	100	92%	11%
AVE	300G	6000	91.6%	10.7%

4.Conclusion

This paper applies extraction algorithm of energy distance vectors of wavelet packet decomposition and BP neural network technology to feature analysis and recognition for active inducing uranium components fission signals on the basis of measurement principles and signal characteristics analysis from active inducing uranium component fission signals. The research result indicates that BP neural network could be taken as an analysis method for detecting uranium components attribution, which has high feasibility in terms of either model constitution or analysis results. The numerical simulation results could provide reference for verification of uranium component attribution in active inducing uranium components, and also offer technical support for further research.

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