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Time-of-flight discrimination between gamma-rays and neutrons by using artificial neural networks

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ABSTRACT

In gamma-ray spectroscopy, a number of neutrons are emitted from the nuclei together with the gamma-rays. These neutrons influence gamma-ray spectra. An obvious method for discrimination between neutrons and gamma-rays is based on the time-of-flight (*tof*) technique. In this work, the *tof* distributions of gamma-rays and neutrons were obtained both experimentally and by using artificial neural networks (ANNs). It was shown that, ANN can correctly classify gamma-ray and neutron events. Also, for highly nonlinear detector response for *tof*, we have constructed consistent empirical physical formulas (EPFs) by appropriate ANNs. These ANN–EPFs can be used to derive further physical functions which could be relevant to discrimination between gamma-rays and neutrons.

1. Introduction

Nuclear spectroscopy closing to the neutron and proton drip-lines is a challenging topic in theoretical and experimental nuclear structure physics. In order to investigate exotic nuclei lying in these regions, heavy-ion fusion–evaporation (HIFE) reactions, which are widely used type of nuclear reactions, are invaluable tool. In these types of reactions, two nuclei fuse to form a compound nucleus. The compound nucleus decays by evaporating numerous light particles, principally neutrons, protons and alphas. Contrary to the charged ones, neutrons can travel long distances and interact inside the detectors together with the gamma-rays. These neutrons cause unwanted background in the gamma-ray spectra.

The issue is accurately identification of neutron interactions in the detectors and determination of individual gamma-rays belonging to the residual nuclei, especially produced with very low intensities. In order to thoroughly overcome detecting the low signals, high-resolution HPGe gamma-ray detectors have been developed (Vetter, 2001; Akkoyun et al., 2012). In the germanium detectors, used in this study, the main energy deposition mechanisms of neutrons following HIFE reactions are elastic and inelastic scatterings. Inelastic scatterings of neutrons are more complex because of excitation of the recoiling germanium nuclei. In order to separate neutrons from gamma-rays, time-of-flight (*tof*) method is an obvious way. This possibility was previously examined in the simulations of the high-resolution HPGe gamma-ray detectors (Ljungvall and Nyberg, 2005; Senyigit et al., 2010).

The physical phenomena involved in *tof* distributions are characteristically highly nonlinear. Therefore, in many cases it may be difficult to construct explicit form of empirical physical formulas (EPFs) for detector response functions. Then, by various appropriate operations of mathematical analysis, derivation of potentially useful highly nonlinear physical functions for *tof* distributions is of utmost interest. Compatibly our previous theoretical treatment (Yıldız, 2005), appropriate EPFs for germanium detector nonlinear responses can be built by using artificial neural networks (ANNs). In this work, we gave a way to obtain *tof* distributions of gamma-rays and neutrons by ANNs. Using ANN method can help classification of gamma-ray and neutron events. We have also constructed consistent EPFs by convenient ANNs.

Recently, ANNs have been successfully used in many fields including discrimination of neutrons and gamma-rays (Cao et al., 1998; Esposito et al., 2004; Liu et al., 2009; Yildiz and Akkoyun, 2013). In this paper, we particularly aim to construct explicit mathematical functional form of ANN–EPFs for nonlinear detector responses for *tof* distributions. While the detector responses were intrinsically highly nonlinear, even so train set ANN–EPFs successfully fitted these responses. Furthermore, test set ANN–EPFs consistently predicted the responses. That is, the physical laws graved in the detector responses data were extracted by the ANN–EPFs.

2. Monte Carlo simulations of HPGe detectors

In the simulations, considering high-resolution gamma-ray detectors (Vetter, 2001; Akkoyun et al., 2012), an HPGe detector is used for measurements of the neutrons and gamma-rays. The

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diameter and thickness of the cylindrical planar detector are 7 and 7.5 cm, respectively. The distance between gamma-ray/neutron source and the front surface of the detector was 25 cm. For the simulations of the detector and the interactions of gamma-rays and neutrons inside the detector, Geant4.9.2 Monte Carlo simulation program (Agostinelli et al., 2003) was used. Neutrons are detected indirectly in the detector via predominantly elastic and inelastic scattering from the germanium nuclei.

In order to obtain *tof* distributions of gamma-rays or/and neutrons, gamma-rays and neutrons were sent to the detectors from the source position, together and one by one. The energies of the incident neutrons with 4 multiplicities were sampled from a distribution (at 0–15 MeV interval) which is obtained from a typical HIFE reaction. The flight times are 58 ns for 100 keV neutrons and 4.5 ns for 15 MeV neutrons to the front face of the detectors. The discrete energies of the gamma-ray cascade with multiplicity 30 are in 1–3 MeV intervals. The flight time of the gamma-rays is about 1 ns. In Fig. 1, *tof* distributions of gamma-rays and neutrons were given. This study aims to give an alternative way to introduce *tof* distributions of gamma-rays and neutrons. Using this information can help classification of gamma-ray and neutron events by using artificial neural network method.

3. Artificial neural networks

3.1. ANN fundamentals

Artificial neural networks (ANNs) are known to be very powerful multivariate tools that are used when standard techniques fail to properly take account of the correlation between these variables. The main task of the ANNs is to give outputs in consequence of the computation of the inputs. ANNs are mathematical models that mimic the human brain. They consist of several processing units called neurons which have adaptive synaptic weights (Haykin, 1999). ANNs are also effective tools for pattern recognition. The classical ANN consists of three layers: input, hidden and output (Fig. 2). The number of hidden layers can differ, but a single hidden layer is enough for efficient nonlinear function approximation (Hornik et al., 1989). In this study, one input layer with one neuron, one hidden layer with many (h) neuron and one output layer with one neuron (1–h–1) ANN topology was used for accurately and reliably prediction of *tof* distributions of the gamma-rays and neutrons. Besides, there are also biases (whose signals are equal to one) connected to the hidden and output layer neurons. The aim of these biases whose signal is equal to one is to scale

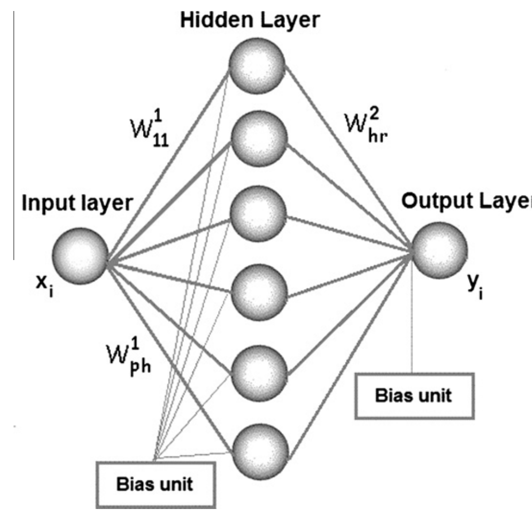

Fig. 2. Fully connected one input-one hidden-one output layer ANN (1–6–1). x_i and y_i are input and output vector components respectively. Circles are neurons and lines indicate adaptable synaptic weights. w^i_{jk}: weight vector component, where i is a layer index, jk weight component from the jth neuron of ith layer and to kth neuron of $(i+1)$th layer. There are also bias units connected to the neurons in the hidden and output layers.

the input to a useful range. Analyses were performed for different hidden neuron numbers, h = 6, 15 and 25. So, the total numbers of adjustable weights/bias were 19, 46 and 76.

The neuron in the input layer collects the data from environment and transmits via weighted connections to the neurons of hidden layer which is needed to approximate any nonlinear function. The hidden neuron activation function can be theoretically any well-behaved nonlinear function. The type of activation function was chosen as hyperbolic tangent for hidden layer (Eq. (1)):

$$\tan h = \frac{(e^x - e^{-x})}{(e^x + e^{-x})} \tag{1}$$

Instead of Eq. (1), any other suitable sigmoidal function could also be used. The output layer neuron returns the signal after the analysis. Note that, an input layer with single neuron is firmly equivalent to one neuron ANN with an appropriate activation function. As far as the activation function is analytical, the output is also an analytical function of the input.

The ANN train and test datasets used in this work were produced by Geant4 simulations which are mentioned in Section 2. At the first step of the simulations, gamma-ray experimental data (dataset-I) and neutron experimental data (dataset-II) were generated separately mainly for training stage. In the last simulation, the data (dataset-III) including both gamma-rays and neutrons together were generated for application of discrimination between gamma-rays and neutrons.

An ANN software NeuroSolutions v6.02 was also used. The ANN input was *tof* values of the gamma rays and/or the neutrons and the desired outputs were detector responses for *tof*. During all ANN processes, the data was normalized into [−1, 1] interval. In the training step, dataset-I and dataset-II were used separately. For all ANN processing case, dataset-I and II were divided into three separate sets. One of this is for the training stage (about 50% of all data), 20% is for validation and the rest is for the test stage. In the training stage, a back-propagation algorithm with Levenberg–Marquardt for the training of the ANN was used. By convenient modifications, ANN modifies its weights until an acceptable error level between predicted and desired outputs is attained. The error function which measures the difference between outputs was *mean square error* (MSE) as given in Eq. (2):

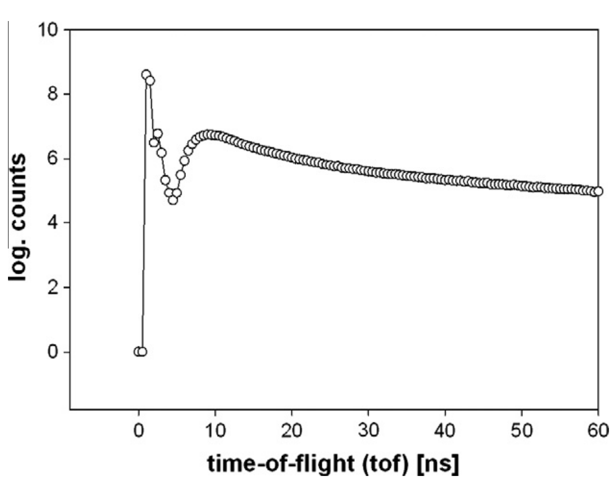

Fig. 1. Time-of-flight (*tof*) distributions of gamma-rays and neutrons in HPGe detectors.