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Explosives detection using prompt-gamma neutron activation and neural networks

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Abstract

This work describes a study of the application of a neural network to determine the presence of explosives using the neutron capture prompt gamma-ray spectra of the substances as patterns which were simulated via Monte Carlo N-particle transport code, version 4B. After the training of the neural networks, it was possible to determine the presence of the C-4 explosive, even when they were occluded by several materials. The neural network was a powerful tool, able to recognize prompt gamma-ray explosive patterns in spite of the presence of occluding materials. Besides that, the network was able to generalize, identify the presence of explosive in cases in which it had not been trained. In that way, it was revealed as a potential tool for in situ inspection systems.

Keywords: Explosives detection; Prompt-gamma neutron activation; Neural networks; Monte Carlo transport code

1. Introduction

Prompt-gamma neutron activation analysis (PGNAA) is a well-known, non-destructive testing method and has been applied for chemical analysis in streams process and laboratories. The basic physics behind PGNAA is well understood (Shea et al, 1990; Hussein and Waller, 1998; Spyrou, 1999). Thermal neutrons are absorbed by many atoms. When thermal neutrons are captured, the resulting compound nucleus typically has an excess of energy. Hence, a nucleus which has absorbed a neutron will promptly emit characteristic gamma-rays of known energies and emission rates (Hussein and Waller, 1998). Inspection of checked airline baggage and buried mines can, therefore, be realized employing a PGNAA-based detection system. In this PGNAA system, the inspected object, for example, a suitcase containing explosive, is conveyed through a cloud of thermal neutron emanating from a source of fast neutrons immersed in a moderator. The penetrating thermal neutrons interact with the contents of the suitcase generating characteristic high-energy gamma-rays such as 10.8 MeV from nitrogen, 2.2 MeV from hydrogen, and so forth. The gamma-rays escape from the suitcase and some of them are detected by many detectors around the luggage. By counting the number of gamma-rays emitted with a specific energy one can deduce the amount of elements contained within the object. Plastic explosives such as C-4 have a very high nitrogen content. Therefore, the intensity of 10.8 MeV gamma-rays detected is an indication of the presence of explosives. A problem with spectrum interpretation is that neutrons are absorbed in the surrounding radiological shielding and some substances rich in hydrogen and nitrogen, which results in a background component that interferes with the signal of interest.

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The purpose of this work is to show the applications of PGNAA and a trained neural network in order to determine the presence of explosives hidden among other innocuous materials, considering a phantom and a neutron beam both idealized. The activated gamma-ray spectrum generated from neutrons absorption by atomic constituent elements of the illicit substances were obtained via Monte Carlo simulation aiming at establishing a data base (fingerprint) to several types of explosives (C-4, Semtex, TNT, etc.) and drugs (cocaine) and they were used in a neural network program to predict the presence of explosives and drugs when concealed by innocuous materials.

2. Monte Carlo simulation

The Monte Carlo code of particle transport MCNP, version 4B (Briesmeister, 1997), was used to generate the capture gamma spectrum resulting from the nuclear interactions of the thermal neutrons (an energy of 0.025 eV) with the chemical elements of which the illicit substances are composed. MCNP is a general purpose Monte Carlo radiation transport code for three-dimensional, continuous energy, time-dependent neutron, photon and electron transport and it was developed at Los Alamos National Laboratory. The Evaluated Nuclear Data File B-VI (ENDF/B-VI) continuous energy neutron cross section library and the MCPLIB02 photon library (DLC-189 XS libraries) were used.

A diagram of the physical layout for a typical MCNP4B run is shown in Fig. 1. It consists of a spherical shaped phantom (explosive, drug, occluding material) of 1 cm^3 which is conveyed through a thermal neutron beam. The neutrons, with an energy of 25 meV, started in a single source plane with an area of $2.5\,cm \times 2.5\,cm$, and were in parallel direction to each other. Electron transport was turned off using the mode card (mode: NP with importances equal to 1). The capture gamma-rays were counted in an external surface of the phantom (in 4π). The counting mode used was concerned with the number of particles which crosses a spherical surface (F1 surface current tally) without any variance reduction. In this way, photons of all energies emitted in all directions are detected, and computational time was minimized. A similar modeling technique was used by Sohrabpour et al. (1999).

3. Neural networks

Neural networks are mathematical models inspired by the human brain, and they possess the capacity to extract knowledge from a group of data previously established (Haykin, 1999). They are composed of several process units, called neurons, whose operation is very simple. The connections among neurons are named synapses. The activation of a neuron depends on the attributed weight of the synapses that are appraised through the activation functions. The behavior of the net, in a certain problem, network behavior is based on the synapse firing frequency. Neural networks require training in which the weights of their synapses are adjusted in agreement with the presented patterns, by doing that they learn through examples. The learning of a network is the adaptation process to the data training, while the training is the adaptation process that makes learning possible. The training has the objective of selecting the weight that adapts better to the net in relation to the presented data, so that it carries out the wanted function (Haykin, 1999).

We used backpropagation algorithm (Haykin, 1999) for the training of feedforward neural network. In that algorithm, the net operates in two stages. In the first one, a pattern is presented to the layer of the net input. Soon after, the resulting activity flows through the net, layer after layer, until the output layer produces the answer. In the following stage, the output is obtained and compared with the wanted output. In the case of those outputs it is different, the error is calculated and, at this point, it is spread from the exit layer to the output layer, modifying the weights of the synapses in the

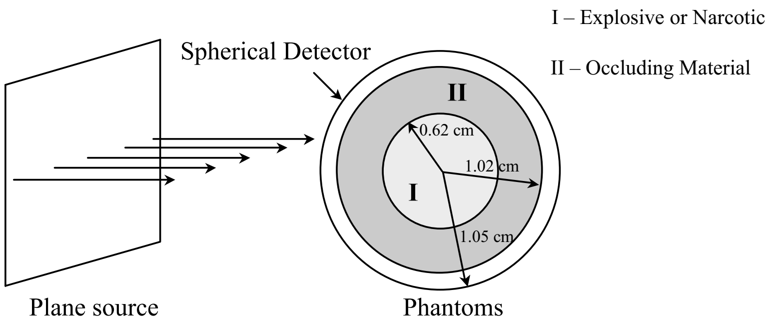

Fig. 1. Geometric configuration of the simulated system.

intermediate layers, while the error is back propagation. The error signal at the output of neuron j at iteration n, $e_j(n)$, is defined by (Haykin, 1999)

$$e_j(n) = d_j(n) - y_j(n), \tag{1}$$

where $d_j(n)$ is the desired response for neuron j and $y_j(n)$ is the function signal appearing at the output of neuron j at iteration n.

The instantaneous value of the error energy for neuron j, $E_j(n)$, (in the nth training example) is defined as (Haykin, 1999)

$$E_j(n) = \frac{1}{2} e_j^2(n). \tag{2}$$

After the energy function is computed (output) by the net, training is backwards propagated and weight values, $w_{ji}(n)$, are modified using the following relation (Haykin, 1999):

$$\Delta w_{ji}(n) = -\eta \frac{\partial E(n)}{\partial w_{ji}(n)}, \tag{3}$$

where η is called the learning factor.

In summary, the data were generated by MCNP, the spectra were used as inputs for training several architectures of neural networks. To train the net, we used backpropagation algorithm. For neural networks, we used NeuroShell v.2.0 (Tutorial NeuroShell 2.0, 1993). This code is a framework ambient project of neural networks, discarding the need for extensive programming.

In the first layer, 100 neurons were used, which correspond to the channels of energy between 1.0 and 11.0 MeV (with 100 equally spaced bins of 0.1 MeV each), and the linear function activation, defined in [−1,1] was applied. In the following layer, was used as activation the logistics function and a total number of 80 neurons. In the last layer, 19 neurons were used, each one of them representing one material given in Table 1, and the chosen activation was also the logistics function. With the aim of obtaining binary answers (0 and 1) without noise, the cut's rule was applied in the first neuron of the last layer at 0.7 value and others, of same layer, at 0.5.

Different chemical formulations were chosen for several materials that can be found inside the

Table 1
Physical density and elementary composition for various substances of interest

Substance of interest	Elementary composition	Physical density (g/cm^3)
Acrylic	$C_{12}H_{12}N_4$	1.19
Aluminum	Al	2.70
Ammonium nitrate	$H_4N_2O_3$	1.66
C-4	$C_4H_6O_6N_6$	1.83
Cellulose	$C_6H_{10}O_5$	1.00
Cocaine	$C_{17}H_{21}NO_4$	1.40
Iron	Fe	7.86
Lead	Pb	11.30
Nitroglycerin	$C_3H_5O_9N_3$	1.59
Nylon	$C_{11}H_{26}O_4N_2$	1.15
PAN	C_3H_3N	1.18
PETN	$C_5H_8O_{12}N_4$	1.77
Polyethylene	CH_2	0.94
PVC	C_2H_3Cl	1.19
Rubber	C_5H_8	0.94
Silk	$C_3H_{11}O_6N_3$	0.30
Sucrose	$C_{11}H_{22}O_{11}$	0.90
TNT	$C_7H_5O_6N_3$	1.65
Water	H_2O	1.00

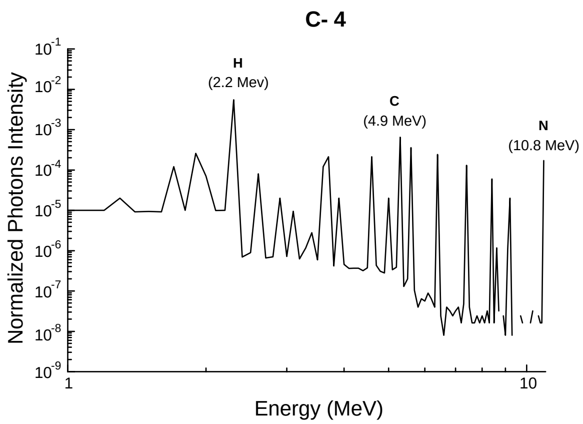

Fig. 2. Prompt gamma-ray spectrum from 1 to 12 MeV generated by MCNP following C-4 irradiation with 25 meV neutrons.

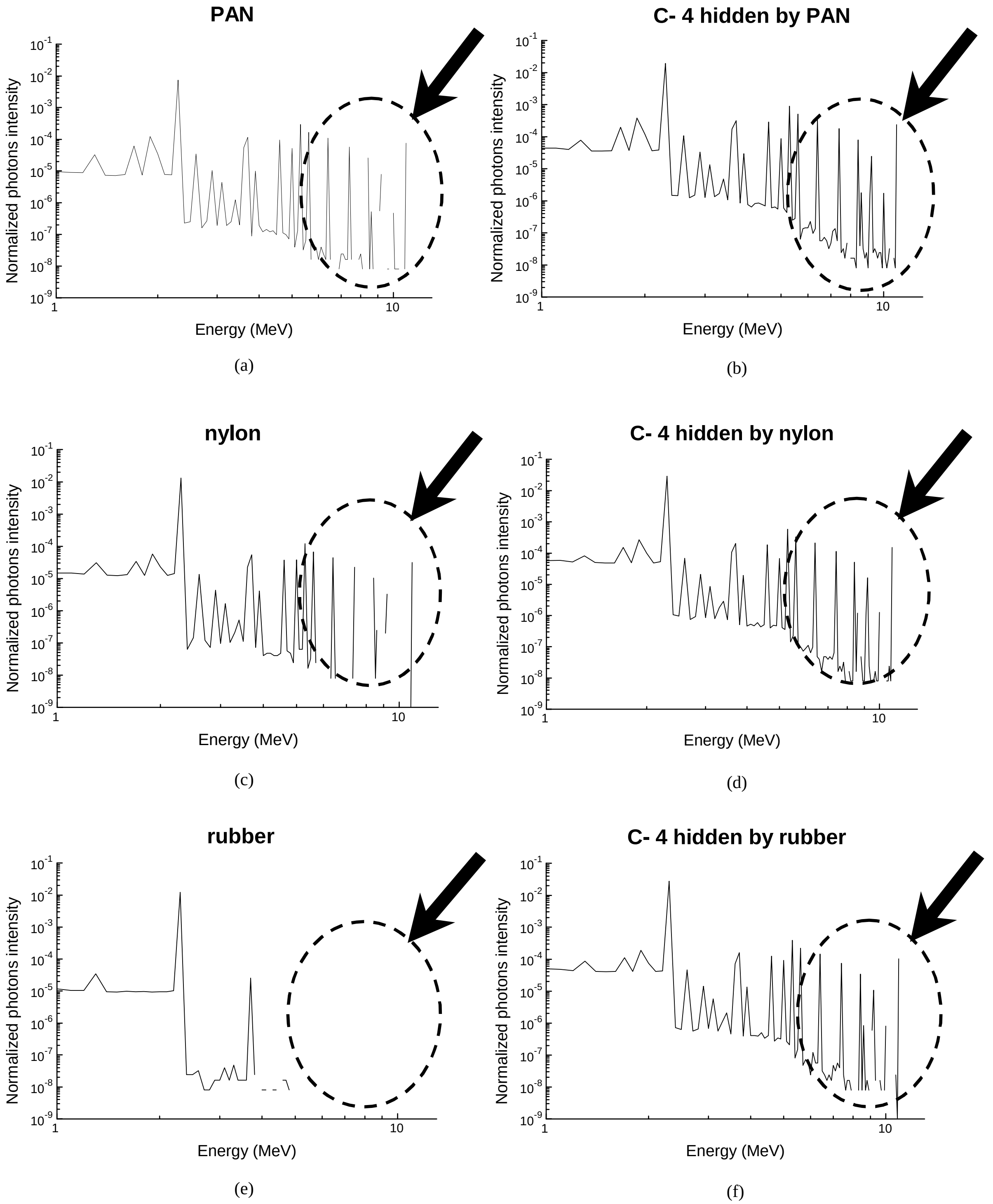

Fig. 3. Gamma-ray spectra of following samples: (a) PAN, (b) C-4 hidden by PAN, (c) nylon, (d) C-4 hidden by nylon, (e) rubber e (f) C-4 hidden by rubber.

passengers' luggages. For each technique, they were simulating the materials that is present in the specialized literature on issue (Miller, 1994; Brown and Gozani, 1996). The list of the materials that were utilized in this work, as well as its chemical compositions and respective densities, are shown in Table 1.

4. Results

In Fig. 2, the gamma-ray spectrum (fingerprint) represents the interactions between the thermal neutrons and the nucleus of the constituent elements of a typical plastic explosive, such as C-4. This spectrum shows the peaks (marked) characteristic due to the prompt gamma-ray of hydrogen (2.2 MeV), carbon (4.9 MeV), and nitrogen (10.8 MeV). For energies from 2 to 11 MeV, the explosive spectra have individual signatures. For investigating the network capacity to identify occluded explosive spectra, unadulterated explosive spectra were presented for training.

In Figs. 3 and 4, formation or absence of peaks beyond 5 MeV is highlighted with an arrow. Similarity among occluded spectra and unadulterated C-4 spectra are demonstrated in parts (b), (d) and (f) of Figs. 3 and 4. This similarity above 5 MeV is not evident in parts (a), (c) and (e) of Figs. 3 and 4.

For neural networks identify patterns whose knowledge was acquired, without any previous difficulty. Evidently in the evaluation of patterns, without the previous knowledge of the net, the probability of the occurrence of the recognition of mistakes increases.

The results obtained from analysis by activation were good. The net was able to identify the presence of C-4 in 97.28% of the test cases, even with occluding materials. The neural network presented the correct classification of the presence of C-4 in 97.28% of the test cases. Another important fact that should be highlighted is that, as 19 different types of substances were studied, in other words, for a reasonable sampling, it is hoped that the net will answer correctly, to a great number of situations. Besides that, it is hoped that it is capable of generalizing the recognition of illicit material's spectra, for a wide range of different occultations.

In item 2, it was commented that the neural network applied for the identification of the spectra range obtained by the code MCNP4B. It possesses 100 neurons in input layer. As we have already predicted, two of the neurons that possessed weights of great importance in the decision of the net, they were associated with the photon energy characteristic of the presence of carbon (4.9 MeV) and nitrogen (10.8 MeV), emitted by neutron's interactions with those atoms. Those referring weights to the carbon and the nitrogen are represented in the graph of the contribution factor, given in Fig. 5. That attribution of importance to the peak of nitrogen resides in the fact that the plastic explosive presents a high concentration of that element, which differentiates it from other materials with hydrogen content. However, materials such as nylon or PAN also possess atoms of nitrogen, but in a much smaller concentration, in relation to the number of atoms of carbon. Likewise, it is important to consider the amounts of carbon and nitrogen present in each phantom, in order to determine the presence of plastic explosives. It means that the neural networks were able to generalize, in cases where the presence of carbon or nitrogen are really important, and determine the presence or absence of C-4, in the cases presented here.

Only in the production file, data never presented to the net, spectra with occluded explosive (occlude C-4 for: rubber, nylon, PVC and PAN) were inserted. That generated a much larger reliability in relation to the capacity of generalization of the network because, although those spectra have never been presented previously, the net answered correctly, indicating the presence of the sample of C-4.

Finally, it is clear in Fig. 5 that some energy ranges (associated with groups of neurons) have an important contribution to the network decision, although it is evident that all neurons contribute to the arising of this decision.

5. Conclusions

This work aimed at detecting plastic explosives, through PGNAA technique, allied to the algorithm of neural networks, that was responsible for the determination of the presence or absence of illicit sample when it hides in different materials, in agreement with the respective simulate modelings for the code MCNP. The results show that for the geometries modeled and neutron energy chosen in simulations it is relatively easy to identify the hidden explosive. The data generated by MCNP provided a great ease in obtaining the number of cases studied in this work and with a high confidence. In that way, it was possible to simulate a larger number of cases and to apply them to the net.

PGNAA have the advantage of generating gamma-rays whose energy is unique characteristic of the target nucleus. For that reason, each spectrum that represented the presence of the explosive sample contained enough information to determe the neural network. In that case, the net demonstrated to learn the pattern that determines the presence of C-4 explosive, even if it is occluded for that materials.

In this way, through the results obtained with 97.28% of identification of the presence of the C-4 sample, it can be affirmed that the neural networks, allied to the PGNAA, is well applied to the detection of occluded explosives by the materials studied in this work, being able to generalize in occultation situations in which it had not been previously trained. The next step in this study is to simulate realistically the phantom sizes (1 m^3 instead of 1 cm^3) and the neutron energy as a poly energetic epithermal neutron source.

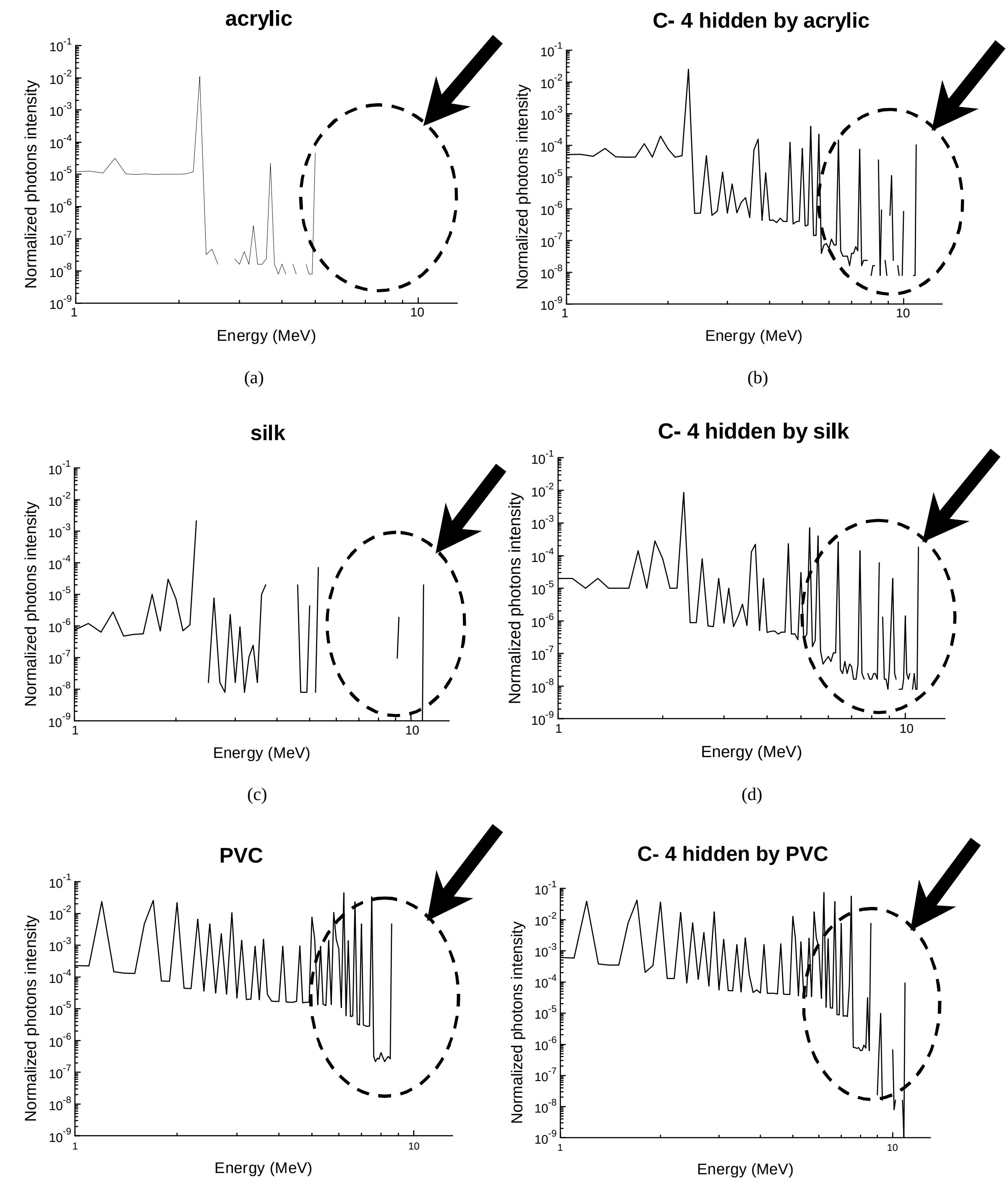

Fig. 4. Gamma-ray spectra of following samples: (a) acrylic, (b) C-4 hidden by acrylic, (c) silk, (d) C-4 hidden by silk, (e) PVC, (f) C-4 hidden by PVC.

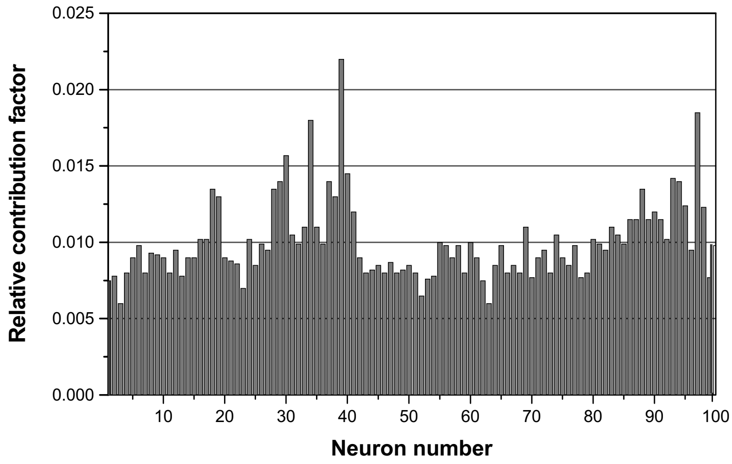

Fig. 5. Neuron signal amplitudes for PGNAA C-4 spectra.

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