

Research Article

Improving Neutron-Gamma Discrimination with Stilbene Organic Scintillation Detector Using Blind Nonnegative Matrix and Tensor Factorization Methods

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In order to perform highly qualified neutron-gamma discrimination in mixed radiation field, we investigate the application of blind source separation methods based on nonnegative matrix and tensor factorization algorithms as new and robust neutron-gamma discrimination software-based approaches. These signal processing tools have allowed to recover original source components from real-world mixture signals which have been recorded at the output of the stilbene scintillation detector. The computation of the performance index of separability of each tested nonnegative algorithm has allowed to select Second-Order NMF algorithm and NTF-2 model as the most efficient techniques for discriminating neutrons and gammas. Furthermore, the neutron-gamma discrimination is highlighted through the computation of the cross-correlation function. The performance of the blind source separation methods has been quantified through the obtained results that prove a good neutron-gamma separation.

1. Introduction

Neutron detection has been applied in many diverse fields from the scientific to industrial. The scintillation detectors [1] are the most adopted for neutron detection and preferred means for neutron spectroscopy purposes. However, their sensitivity to gamma-rays disturbs the estimation accuracies of the neutron pulses [1]. Within this framework, various researches have been done using digital and analog techniques to discriminate neutrons from the background gamma-rays. Due to their specific feature of organic scintillation and varying quality of discrimination, pulse shape discrimination (PSD) methods were commonly used to perform the neutron-gamma discrimination [2]. The most popular ones are charge comparison [3], rise time [4], zero-crossing [4] as PSD conventional methods, and pulse gradient analysis (PGA) as PSD digital one [5]. The quality of neutron-gamma discrimination using these standard PSD

methods has been quantified by Figure of Merit (FOM) metric. A high FOM value is interpreted as a good discriminator between the pulses generated by neutrons and gamma-rays. Nevertheless, in the presence of pulse pile-up, FOM is not able to well discriminate the gamma contribution and can be a little misleading [6]. Thus, we can say that the PSD methods are insufficient to perform the separation task with high precision.

With the progress of digital pulse processing (DSP) tools and in order to improve the accuracy of neutron-gamma discrimination, novel approach-based on blind source separation has been proposed known as the most popular unsupervised learning techniques. We have used in our previous works, the Nonnegative Matrix Factorization (NMF) methods to analyze fission chamber's output signals, produced using simulation codes, for neutron flux monitoring purpose [7]. The Nonnegative Tensor Factorization (NTF) algorithms has been applied by Laassiri et al. to

recover the original sources from simulated signals recorded by fission chambers in order to achieve the neutron-gamma discrimination task [8].

The main objective of this work is to analyze the output signals of stilbene scintillation detector, through both NMF and NTF techniques, in order to extract the original independent sources, also called Independent Components (ICs). The computation of the performance index of separability (PI) of each NMF and NTF algorithm allows selecting the most efficient one. The extracted sources will be characterized using cross-correlation function as an object function to separate neutrons from gamma-rays background.

This paper is organized as follows. The first part consists of describing the theory of the blind source separation methods (Section 2). Secondly, we briefly present the experimental setup employed to obtain the datasets used in this work (Section 3). Then, we develop our new discrimination approach based on blind source separation techniques (Section 4). At last, the obtained results will be illustrated (Section 5).

2. Blind Nonnegative Matrix and Tensor Factorization Methods

In this work, we tackle the neutron-gamma discrimination problem from a Blind Source Separation (BSS) point of view. In general, the BSS regroups the methods used to solve the problem of recovering mutually independent components, called sources, from a set measured sensor signals (or observations). These last are mixtures formed through an unknown system, during the propagation of the information from its original sources to sensors in addition to the background noise introduced by the sensors themselves.

Indeed, we have decided to use NMF and NTF methods in order to extract the ICs from signals recorded at the output of stilbene scintillation detector. The computation of the PI values of each NMF and NTF algorithms allows selecting the most appropriate one and is suitable to analyze our set of nuclear data. This selection is confirmed through the measure of the signal-to-interference ratio (SIR) that is determined the accuracy of the sources separation. Furthermore, the computation of the cross-correlation function between the extracted ICs and pure neutron and gamma signals allows us to achieve a better characterization of the neutron and gamma-ray signals.

The ability of our proposed methods to recover the original sources from observed mixtures without any requirements on the analyzed mixtures or the mixing process enables us to apply them under any neutron and gamma energy ranges. Moreover, the dimensionality reduction sought in many applications and the nonnegativity constraints allow better-modeled and interpreted neutron and gamma signals with ideally sparse or smooth components.

2.1. Nonnegative Matrix Factorization. The main goal of the NMF is to find lower-rank nonnegative matrices for recovering the sources (or hidden components) with specific

structures and physical interpretations. The recovered sources are then characterized through the computation of the cross-correlation function to perform the neutron-gamma discrimination. The high performance of this function for evaluating the degree to which two signals are similar and its computation simplicity are two main reasons behind chosen cross-correlation function to perform the discrimination purpose.

Many researchers, e.g., Paatero and Tapper [9] have investigated the NMF methods, but they have only acquired popularity since the publication of the works of Lee and Seung [10, 11]. They have proposed a simple multiplicative update algorithm to find nonnegative representations of nonnegative signals and images [10]. The nonnegativity constraint is usually presented as the origin of the NMF robustness to provide a perceptual decomposition of the data.

The NMF [12] is an analogous technique of linear algebra for reducing the ranks of matrices with positive value atoms that can be more easily interpretable and semantically more relevant. The NMF approximates Y as a product between two matrices null or positive as follows [12]:

$$Y = AX + E, \quad (1)$$

where

- (i) $Y = [y_{mt}] = [y(1), y(2), \dots, y(T)] \in \mathfrak{R}_+^{M \times T}$ is the matrix of observed data, with M being mixed signal and T being corresponding number of samples,
- (ii) $A = [a_{mr}] = [a(1), a(2), \dots, a(R)] \in \mathfrak{R}_+^{M \times R}$ is a mixing matrix with $a_{mr} \geq 0$, with R being number of estimated components,
- (iii) $X = [x_{rt}] = [x(1), x(2), \dots, x(T)] \in \mathfrak{R}_+^{R \times T}$ is the matrix of original nonnegative sources with $x_{rt} \geq 0$,
- (iv) $E \in \mathfrak{R}^{M \times T}$ is a noise or error matrix.

The standard approach to NMF is the alternating minimization of a specific cost function [13]. It is presented in the Appendix A of this paper.

2.2. Nonnegative Tensor Factorization. For some applications, the matrices are considered as second-order tensors. Usually, they can go up to the third or higher order. Thus, the NMF can be generalized to the NTF.

The NTF is a technique for decomposing and computing a nonnegative parts-based representation of high-dimensional data (tensor) into sparse and reasonably interpretable components with the constraint of the nonnegativity. It has been successfully applied to numerous data analysis problems in various fields [14, 15]. The multiway data is one of the important methods of the NTF decomposition. From the point of view of data analysis, the NTF is very interesting because it takes into account the spatial and temporal correlations between the variables accurately more precise [16].

The NTF problem is based on a nonnegative canonical decomposition/parallel factor decomposition denoted by CANDECAMP and PARAFAC, respectively, [17] and

imposes nonnegative constraints on tensor and factor matrices. The mathematical formalism of NTF is as follows [12, 18].

Given an N -th order data tensor and a positive integer J , factorize $\underline{Y} \in \mathfrak{R}^{I_1 \times I_2 \times \dots \times I_N}$ into a set of N nonnegative component matrices $A_j^{(n)} = [a_1^{(n)}, a_2^{(n)}, \dots, a_j^{(n)}] \in \mathfrak{R}_+^{I_n \times J}$, ($n = 1, 2, \dots, N$) representing loading matrices (or factors), that can be expressed as:

$$\begin{aligned} \underline{Y} &= \hat{\underline{Y}} + \underline{E}, \\ \underline{Y} &= \sum_{j=1}^J a_j^{(1)} \circ a_j^{(2)} \circ \dots \circ a_j^{(N)} + \underline{E}, \\ \underline{Y} &= \underline{I} \times_1 A^{(1)} \times_2 A^{(2)} \times \dots \times_N A^{(N)} + \underline{E}, \\ \underline{Y} &= \llbracket A^{(1)}, A^{(2)}, \dots, A^{(N)} \rrbracket + \underline{E}. \end{aligned} \quad (2)$$

With $\|a_j^{(n)}\|_2 = 1$ for $n = 1, 2, \dots, N-1$ and $j = 1, 2, \dots, J$ and \circ is the outer product of the tensors.

The tensor \underline{E} is an approximation error and \underline{I} is the identity tensor. Figure 1 illustrates the decomposition for a third-order tensor.

As mentioned in the NMF section, the computation of nonnegative component matrices is performed usually through the minimization of a suitable design cost function.

NTF-1 and NTF-2 are two NTF models which are implemented under the NTFLab Toolbox (version 1.2) [7, 12] used in the second part of our tests. The selection of the model to be applied is dependent on the form of the observation vectors; since our observation vectors are column ones, the NTF-2 will be more appropriate. The dual model to the NTF-1 is referred to as the 3D NTF-2 (by analogy to the PARAFAC2 model) [12, 19]. The NTF-2 Model can be extended to the decomposition of multiway arrays with different dimensions using the simultaneous factorizations.

A given tensor $\underline{Y} \in \mathfrak{R}_+^{I \times T \times Q}$ is decomposed into a set of matrices $\{A_1, A_2, \dots, A_Q\}$, $X = B^T$ and C with nonnegative entries, by the three-way NTF-2 Model as a slice factorization form [13]:

$$Y_q = A_q D_q X + E_q, \quad q = 1, 2, \dots, Q, \quad (3)$$

where

- (i) $Y_q = \mathbf{Y}_{::q} = [y_{itq}] \in \mathfrak{R}_+^{I \times T}$ are the frontal slices of a 3D tensor $\underline{Y} \in \mathfrak{R}_+^{I \times T \times Q}$;
- (ii) Q is the number of frontals slices;
- (iii) $A_q = [a_{ijq}] \in \mathfrak{R}_+^{I \times J}$ are the basis (mixing) matrices;
- (iv) $D_q \in \mathfrak{R}_+^{J \times J}$ is diagonal matrix that holds the q -th row of $C \in \mathfrak{R}_+^{Q \times J}$ in its main diagonal;
- (v) $X = [x_{jt}] \in \mathfrak{R}_+^{J \times T}$ is a matrix representing latent sources (or hidden components or common factors);
- (vi) $E_q = \mathbf{E}_{::q} \in \mathfrak{R}_+^{I \times T}$ is the q^{th} frontal slice of a tensor $\underline{E} \in \mathfrak{R}_+^{I \times T \times Q}$ comprising error or noise depending on the application.

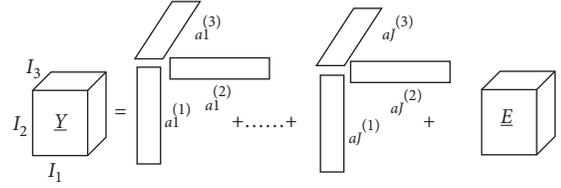


FIGURE 1: Decomposition of 3D tensor into three nonnegative matrices using the standard NTF model.

3. Materials and Methods

In this section, we present the configuration experiment of this research work and our proposed approach to improve the quality of neutron-gamma discrimination.

3.1. Experimental Setup. In this paper, we used stilbene scintillation detector with 45×45 mm crystal and Californium source (Cf-252) as the neutron-gamma radiation source [20]. The stilbene detector composes of a scintillator and a photomultiplier tube (PMT) type RCA7265 [21]. The photomultiplier output is connected directly to the pre-amplifier matched to the coaxial cable whose characteristic impedance is 50Ω . The advanced digital data processing allows reducing the spectrometric acquisition system using numeric samples at the output of the digitizer. To sample pulses for accurate discrimination, a digitizer with at least 200 MS/s is the most appropriate one that fulfills that need. The data acquisition system is composed of a numerical interface Acqiris DP210 with 8 bits resolution, sampling rate of 1 GSample/sec, and a computer where the data are stored for offline processing according to the processing approach described thereafter. Figure 2 depicts our digital apparatus. The output signal of the used detector looks like the one in Figure 3.

3.2. Processing Approach. In this work, we have considered the output signals of stilbene scintillation detector (real world data) as time series mixtures (observations), and we have processed them through nonnegative blind sources separation algorithms. The schematic diagram of Figure 4 summarizes the approach we followed in our tests.

According to the literature, 5 observations is the ideal number of signals to be analyzed that allows an excellent reconstruction of the original sources [22]. Also, we have shown in our previous work [23] that the best number of observation to be processed by BSS algorithm is 5 too. Thus, in this work, we consider a set of 10 real-world preamplifier output signals of a stilbene detector. These signals are structured in 6 matrices of 5 by 1000 mixtures (i.e., $M=5$ and $T=1000$) as shown in Figure 5.

To apply the NMF and NTF algorithms to the recorded signals, we have used the NTFLab Toolbox (version 1.2) which is implemented under MATLAB®7.10 platform [17, 24]. The selection of the most suitable algorithm is based on the computation of the PI [17, 24, 25]. Indeed, the lowest PI value reflects the efficiency of the algorithm to achieve

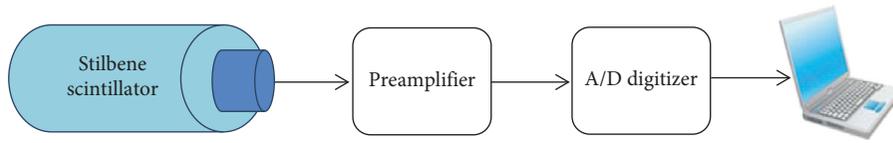


FIGURE 2: Block diagram of experimental setup.

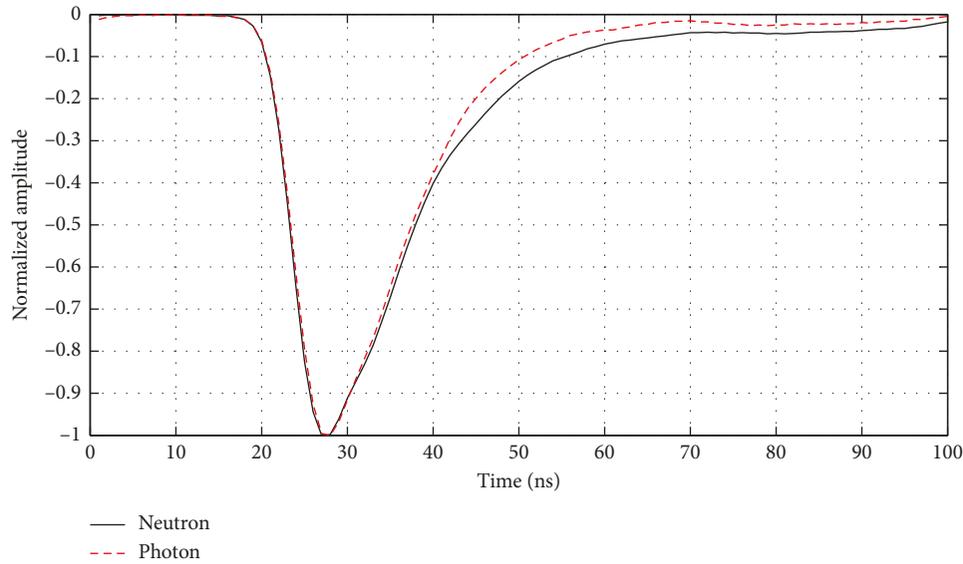


FIGURE 3: Sample of the recorded stilbene output signal. Sample smoothed neutron (solid) and photon (dashed) signals recorded by stilbene scintillation detector, the trailing edge of photon decays faster than that of neutron.

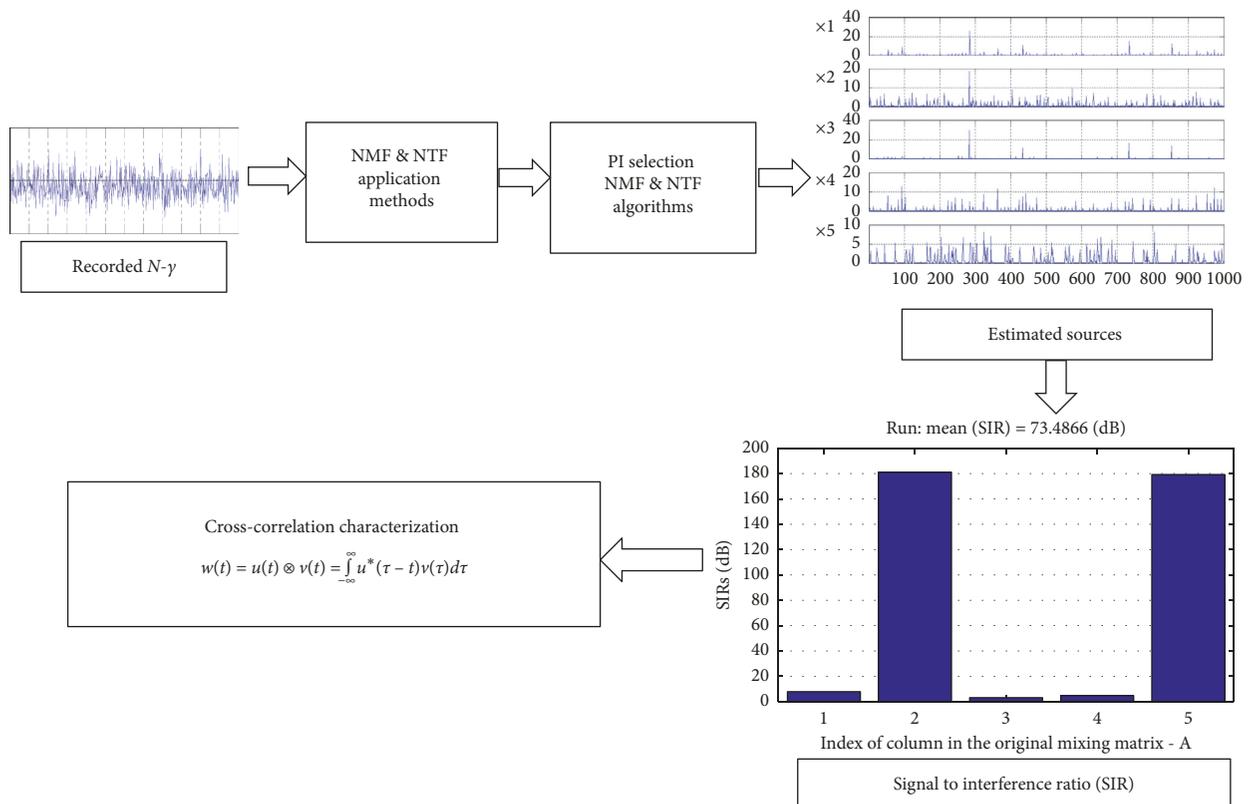


FIGURE 4: Flow chart of the proposed approach.

Matrix Y1 ==>	Obs1	Obs2	Obs3	Obs4	Obs5					
Matrix Y2 ==>		Obs2	Obs3	Obs4	Obs5	Obs6				
Matrix Y3 ==>			Obs3	Obs4	Obs5	Obs6	Obs7			
Matrix Y4 ==>				Obs4	Obs5	Obs6	Obs7	Obs8		
Matrix Y5 ==>					Obs5	Obs6	Obs7	Obs8	Obs9	
Matrix Y6 ==>						Obs6	Obs7	Obs8	Obs9	Obs10

FIGURE 5: Construction of the observation matrices Y.

recovering original source signals and thus its suitability to analyze our dataset [25].

In addition, for each tested NMF/NTF algorithm, the toolbox provides the measure of the SIR. This last is computed according to the columns of the estimated mixing matrix (full rank 5 by 5 matrices). The SIR allows us to check the number of estimated sources which are combined to form the detector output signals, in addition to determining quantitatively the accuracy of the blind source separation task.

Usually, it is assumed that $SIR \geq 20$ dB provides a quite good separation performance. The perfect reconstruction of the original sources (i.e., the solution of $Y=AX$) can be obtained when the $SIR \geq 30$ dB [26]. The reconstruction is a procedure that achieved when the blind separation of signals is performed from an analyzed mixture. It is indeed allowed to extract and remove one or more nonnegative components [25].

Finally, we characterize each recovered source via the computation of the cross correlation between it and a pure neutron and gamma signals. This will allow us to discriminate both of these sources according to the neutron or gamma signal.

4. Results and Discussion

The results of the proposed approach are presented in this section. We recall that our approach involves the application of the appropriate NMF and NTF algorithms in order to extract the original source signals which form the recorded nuclear signals at stilbene output.

4.1. Application of Nonnegative Matrix Factorization. We used the toolbox NMFLAB-SP, which implemented 11 different algorithms; 8 algorithms were tested since 3 are classical BSS algorithms which have not been considered in our work; they have been added to compare performance of NMF algorithms with classical BSS/ICA methods. During tests, 7 NMF algorithms have shown PI values that vary while repeating the test. Consequently, they have been considered unstable and inappropriate to analyze our observations. Thereby, the remaining NMF algorithm is the most stable and effective method ($PI = 0.384$) to perform the separation task of the recorded signals. This algorithm is called Second Order NMF.

The robustness and high performance of the Second-Order NMF algorithm have been demonstrated using real-world data (or experimental data). In fact, this algorithm uses the Quasi-Newton iteration to update the mixing matrix A and the Fixed Point Regularized Least Squares

algorithm for computing the vector of estimated sources X [15, 27, 28]. The application of the Second-Order NMF algorithm based on Quasi-Newton method allows solving our blind source separation problem [17, 27].

The computation of the SIR shows that all recorded signals are formed by two main independent sources, namely, the 2nd and the 5th ones (Figure 6). These two components show high SIR values of about 180 dB, which reflect an excellent reconstruction of the original sources despite the background noise at the preamplifier's output.

The characterization of the obtained recovered sources through cross-correlation calculation has been performed using both pure neutron and gamma signals. As depicted in Figure 7, the 5th IC is strongly correlated with a neutron signal, whereas the 2nd is correlated to the gamma signal. These results confirm that the Second-Order NMF algorithm leads to successful and efficient neutron-gamma discrimination.

4.2. Application of Nonnegative Tensor Factorization. As for the NMF methods, we used the same recorded data. However, the application of the NTF2 model needs to form 3D tensors of overlapped sources. For this reason, we have formed our mixtures (observations) for which the nonnegative dependent 5 hidden components or sources are collected in one slice $X \in \mathbb{R}_+^{5 \times 1000}$. The sources have been mixed by a common random matrix $A_k \in \mathbb{R}_+^{10 \times 5}$ with a uniform distribution. Therefore, we obtained the 3D tensor $\underline{Y} \in \mathbb{R}_+^{10 \times 1000 \times 5}$ of overlapped sources.

The application of the NTF-2 Model to our dataset confirms the results obtained with the Second-Order NMF method. The plot of the SIR of individual columns of the estimated mixing 3D tensors (Figure 8) shows that all recorded signals are also formed by two main ICs.

The characterization of these two components show that the 5th estimated IC is strongly correlated to neutron signal, whereas the 2nd IC is correlated to the gamma signal (Figure 9). These results are consistent with those obtained previously using the NMF method. Once again, the neutron-gamma discrimination has been well performed.

From quality point of view, the NTF-2 Model is more efficient than the Second-Order NMF algorithm. Indeed, the NTF-2 has best SIR values (mean $(SIR_{NMF}) = 7.705$ dB and mean $(SIR_{NTF}) = 13.792$ dB). The SIR has been computed for each IC extracted via both methods. This quality performance can be explained by the fact that tensor factorization methods use multiple projection matrices (3D projections in our case) and thus the separation task is more precise than using 2D projection matrices in the case of the use of NMF methods.

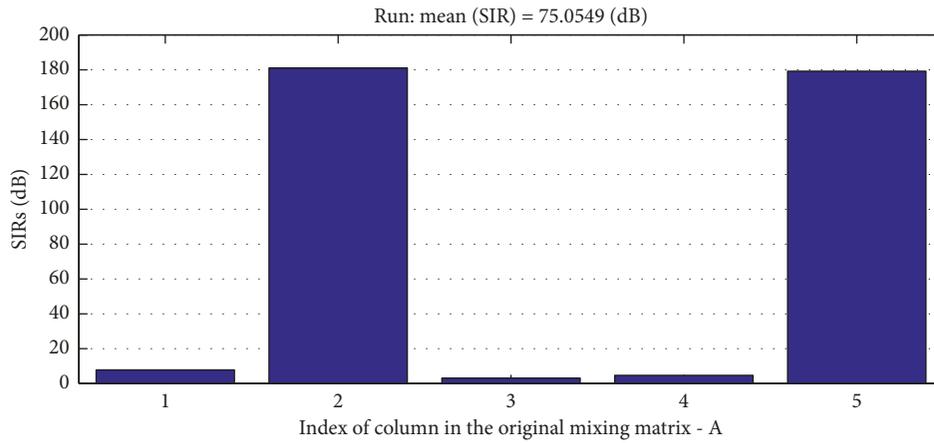


FIGURE 6: Computed values of SIR corresponding to the application of Second-Order NMF Algorithm to experimental nuclear data.

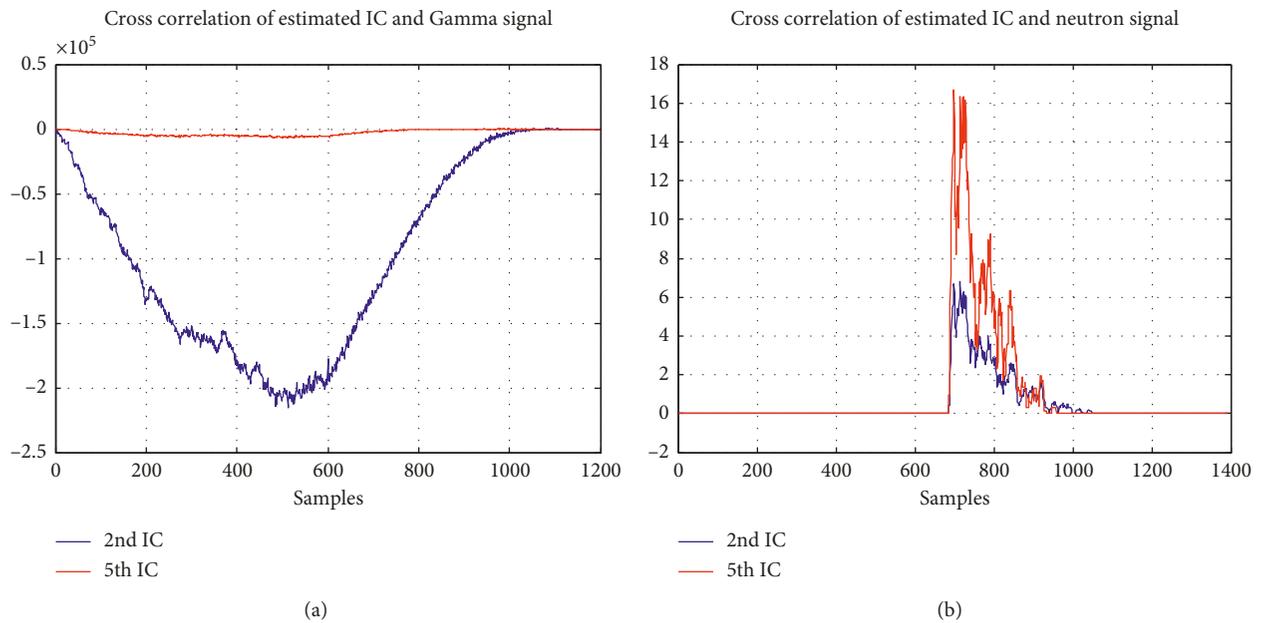


FIGURE 7: Cross correlations between pure gamma (a) and neutron (b) signals and the 2nd and 5th recovered ICs.

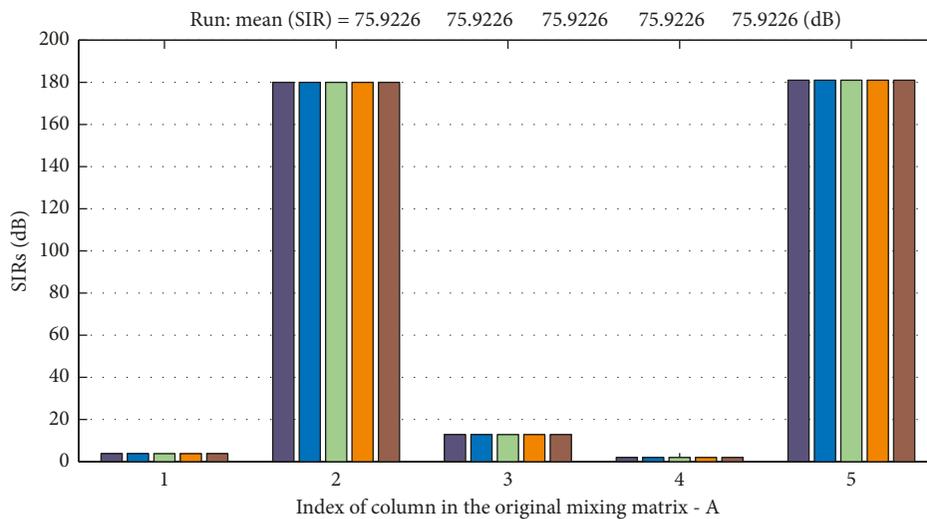


FIGURE 8: SIR of individual columns of the estimated mixing 3D tensors.

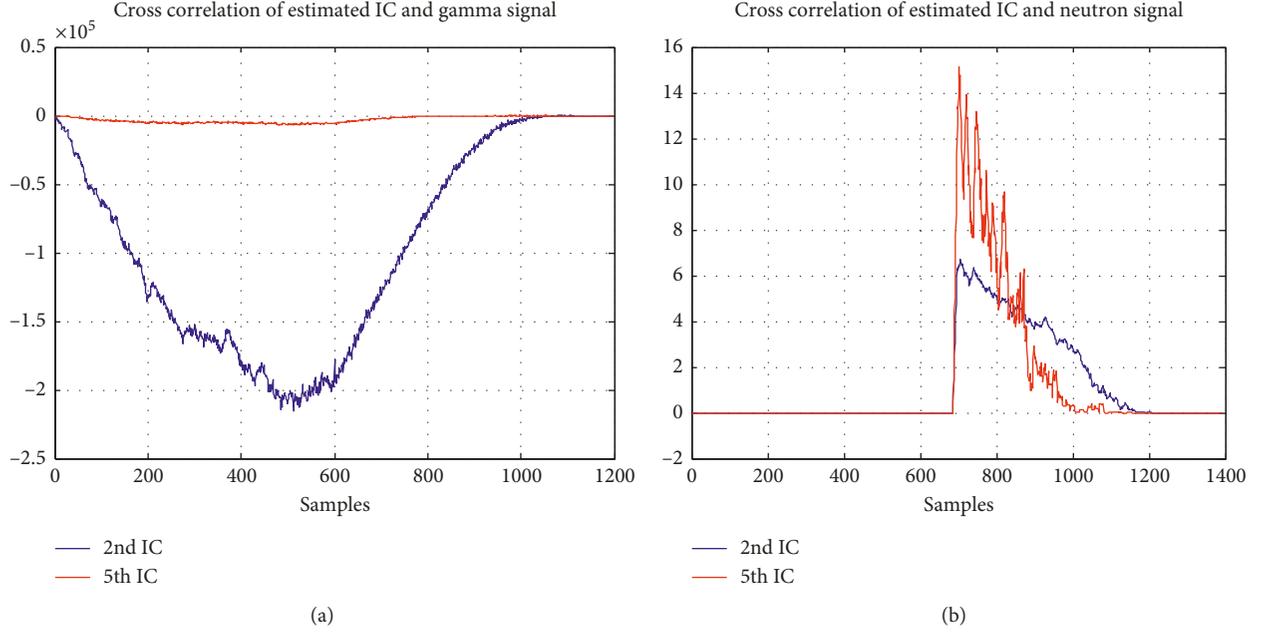


FIGURE 9: Plot of the cross correlations between pure gamma (a) and neutron (b) signals and the 2nd and 5th recovered ICs.

```

Set Randomly initialize:  $A^{(0)}, X^{(0)}$ ,
For  $s = 1, 2, \dots$ , until convergence do
Step 1:
 $X^{(s+1)} = \arg \min_{X, r_{ij} \geq 0} D(Y \| A^{(s)} X) |_{X^{(s)}}$ 
Step 2:
 $A^{(s+1)} = \arg \min_{A, a_{mr} \geq 0} \tilde{D}(Y \| A X^{(s+1)}) |_{A^{(s)}}$ 
End

```

ALGORITHM 1: NMF general form.

```

Input: set of  $Q$  matrices  $Y_q \in \mathfrak{R}_+^{I \times T_q}$ ; input data,  $J$ ; number of basis components
Output: factor  $A \in \mathfrak{R}_+^{I \times J}$  and set of factors  $X_q \in \mathfrak{R}_+^{J \times T_q}$ ,  $q = 1, 2, \dots, Q$ 
Such that the suitable cost functions are minimized.
begin
 $l = 0$  /* number of layers */
 $X_q^{(l)} = Y_q, \forall q, A = I$ 
repeat
 $l \leftarrow l + 1$ 
Initial randomly  $X_q^{(l)}, \forall q$  and/or  $A^{(l)}$ 
/* Minimize alternatively with suitable cost functions */
 $A^{(l)} \leftarrow \arg \min_{A^{(l)} \geq 0} \left\{ D^{(A)}(\bar{X}^{(l-1)} \| A^{(l)} \bar{X}^{(l)}) \right\}$ ,  $a_{ij}^{(l)} \leftarrow a_{ij}^{(l)} / \sum_{i \in S_l} a_{ij}^{(l)}$ 
 $X_q^{(l)} \leftarrow \arg \min_{X_q^{(l)} \geq 0} \left\{ D_q^{(X)}(\bar{X}_q^{(l-1)} \| A^{(l)} \bar{X}_q^{(l)}) \right\}$ ,  $q = 1, \dots, Q$ 
 $A \leftarrow A A^{(l)}$ 
until a stopping criterion is met /* convergence condition */
 $X_q = X_q^{(l)}, \forall q$ 
end

```

ALGORITHM 2: Multilayer NTF1.

5. Conclusion

In this paper, we have used new digital signal processing methods in order to achieve neutron-gamma discrimination

as accurately as possible. The originality of our research work consists of the application of the NMF and NTF methods to solve the neutron-gamma discrimination problem at the output of stilbene organic scintillation detector. The

accomplished tests show that the Second-Order NMF algorithm and the NTF-2 Model are the most effective NMF and NTF methods, respectively, that allow achieving the discrimination task. The obtained results approve that the analyzed real world signals are formed by two main independent components. The computation of the cross-correlation function between these recovered ICs and both pure neutron and gamma signals allows us to discriminate neutrons and gamma-rays accurately. Moreover, the NTF-2 Model is still more efficient than the Second-Order NMF algorithm, since it provides better Signal-to-Interference values (mean (SIR_{NMF}) = 7.705 dB Vs mean (SIR_{NTF}) = 13.792 dB).

Finally, both proposed blind source separation methods provide highly qualified and promising results on software based neutron-gamma discrimination.

Appendix

A. Standard Approach to NMF

Standard approach to NMF is given in Algorithm 1.

B. Multilayer NTF1

Multilayer NTF1 is given in Algorithm 2.

$$\bar{X}^{(l)} = [X_1^{(l)}, X_2^{(l)}, \dots, X_Q^{(l)}]. \quad (\text{B.1})$$

Note that the NTF2 model can be obtained from the NTF1 model by performing matrix transposes.

Data Availability

The datasets generated during and/or analyzed during the current study are not publicly available and will not be shared, due to confidentiality and sensitivity of nuclear data.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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