Blind Source Extraction of HPGe Preamplifier’s Output Signals Using the ThinICA Algorithm: Detection and Identification of Gamma Ray Emitters

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Abstract

In this study, the thin independent component analysis algorithm is used to solve the blind source extraction problem in the case where the observed mixtures are defined as the HPGe preamplifier’s output signals. These last correspond to the response of the detector to a combination of gamma radiation emitters having different levels of radioactivity. Indeed, on the basis of the performance index values, we conclude that this algorithm is the best blind source extraction method to analyze our data. Once the separation task is achieved, we evaluate the signal to noise ratio from individual columns of the mixing matrix. The values of this parameter permit us to detect easily the number of radionuclides used in the

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experiment. Also, we calculate and plot the correlation functions between the signals recorded using one radioactive element and the extracted independent components. The interpretation of the gotten graphics allows us to associate each estimated independent component to the appropriate gamma radiation emitter.

**Keywords**: Blind source extraction, Correlation, Gamma ray emitter, SNR/SIR, ThinICA

### 1. Introduction

Blind signal extraction (BSE) is expressed as the problem of estimating one or a selected number of independent components that appear linearly combined in a set of measured observations [1], [2]. As shown in the figure 1 below, we can formulate the BSE problem using matrix form, as follows:

\[ x(k) = A s(k) + v(k) \quad (eq.1) \]

where:
- \( x(k) = [x_1(k), x_2(k), \ldots, x_m(k)]^T \) is a complex vector of \( m \) observations;
- \( s(k) = [s_1(k), s_2(k), \ldots, s_n(k)]^T \) represents the vector of \( n \) independent components to be estimated;
- \( v(t) \) is an additive noise vector.

![Figure 1: Bloc diagram illustrating the basic BSE problem](image)

Each observation \( x_i(k) \) is assumed to be an instantaneous mixture of \( m \) unknown components or sources \( s_i(k) \), using the unknown \( n \)-by-\( m \) mixing matrix \( A \), [1], [2].

As it is defined in [1], the BSE methods aim to identify the corresponding vector(s) \( \hat{a}_j \) of the mixing matrix \( \hat{A} \) and/or their pseudo-inverses \( \hat{w}_j \) which form the separating matrix rows \( (W = \hat{A}^-) \), assuming only the statistical independence of its primary sources and linear independence of the columns of the matrix \( A \), [1], [2].
In the last decade, the BSE methods have been increasingly used in large number of applications in diverse fields. In fact, in comparison with the blind source separation methods (BSS), which permit to estimate all original sources even if they are not completely mutually statistically independent, the BSE ones allow the decomposition of the observations into only few desired components with particular statistical properties and discard the rest of the uninteresting sources and noises [1], [2].

Many algorithms have been developed to solve the BSE problem such as described in [1], [2], [3], [4], [5], [6], [7], [8]. In this paper, we propose to use the ThinICA algorithm [2], [3], [4], to perform simultaneous extraction of sources from a set of preamplifiers’ output signals of an HPGe detector. This last was exposed to a number of radioelements emitting gamma radiations with different levels of radioactivity. Like most simultaneous extraction methods, this algorithm is flexible and has high performance in terms of separability as the robust blind extraction one [2], [3], [4]. Our main objective is to detect and to identify the used gamma radiation emitters on the basis of the extracted independent components.

2. Material and Method

2.1. Signal database

The experiments involve exposing simultaneously the HPGe detector to different combination of 3 radioactive sources emitting. We used 12 radioactive calibration sources with different levels of radioactivity. During each test, we recorded 60 signals of size of 300 samples each. Indeed, we used a high performance digital oscilloscope (Model Fluke Scope Meter 192B) [9], to record the preamplifier’s output signals of a reverse electrode coaxial HPGe detector (Model GR 3019) [10], at a sampling frequency of 100MHz. in this article we illustrate the results obtained while using a combination of three radioelements: Europium $^{152}$Eu, Sodium $^{22}$Na and the Cadmium $^{109}$Cd.

2.2. The ThinICA algorithm

Thin algorithm for Independent Component Analysis (ThinICA) has been developed by S. Cruces and A. Cichocki [2], [3], [4], to allow simultaneous extraction of arbitrary number of components defined by the user [9]. It performs mutually maximization of several cumulants of the results and/or second order time delay covariance matrices, using a criteria based on contrast function. This last combines the flexibility of the BSE methods with the robustness of the joint approximate diagonalization of BSS one [2], [3], [4], [11]. As shown in [2], [3], [4], the maximization step leads to hierarchical and simultaneous ICA extraction algorithms which are respectively based on the thin QR and thin SVD.
factorizations. This suggests that the ThinICA algorithm can be viewed as hierarchical/simultaneous extensions of the fast fixed point algorithms [2], [3], [4], [11]. The implementation of the ThinICA algorithm is summarized in [3]. In our application, we used its implementation under the Non-negative Matrix Factorization Toolbox (NTFLab) [11].

3. Application to Detection and Identification of γ-Ray Emitters

The computed performance index of separability [1] permits us to confirm that the ThinICA algorithm is the most effective BSE method to analyze our recorded signals (mean PI=0.36842).

3.1. Detection of the number of radioelements

After executing an algorithm, the NTFLab toolbox allows getting several figures of the results of the application of the chosen algorithm. Among them, we exploit the plot of signal to noise or interference ratio (SNR/SIR) of individual columns of the mixing matrix A. It allows the determination number of gamma emitters that we used in each test. Indeed, by definition, a positive value of the SNR indicates that the noise is very low than the real information of the signal. On the contrary, a negative SNR involves that the corresponding independent component matches mostly the noise process. As illustrated in Figure 2 below, the number of columns of the matrix A having positive SNR/SIR values corresponds to the number of radionuclides to which the detector is exposed at each experiment.
3.2. Identification of radioelements

In order to identify the radioelements, we calculate the correlation between each extracted independent component and the recorded preamplifier’s output signal corresponding to the use of one radioactive source. In the following section, we illustrate the results obtained while applying the ThinICA algorithm to mixtures recorded using the three radioelements ($^{152}$Eu, $^{22}$Na and $^{109}$Cd).

The following figure 3.a shows that the observation corresponding to the Europium $^{152}$Eu is strongly correlated with the first extracted independent component. We exclude this component from the list of estimated sources and we redo the same test. We compare the remaining extracted sources to the signal.
obtained using the Sodium $^{22}$Na. This last looks like the 3$^{rd}$ independent source as illustrated by the figure 3.b. We reiterate this process; we found that the 2$^{nd}$ estimated source is highly correlated to a signal resulting from the use of Cadmium $^{109}$Cd as gamma emitter (see figure 3.c).

4. Conclusion

In this study, the performance index values permit us to conclude that the thin independent component analysis algorithm (ThinICA) is the best blind source extraction method to analyze the outputs of HPGe which we exposed to a combination of three gamma radiation emitters having different levels of radioactivity. The calculation of the signal to noise ratio of individual columns of the mixing matrix $A$ allows us to detect easily the number of radionuclides presented to the detector. Thus, the number of positive SNR values corresponds to the number of radionuclides used in the experiments. In addition, the computation of the correlation functions between the signals recorded using one radionuclide and the extracted independent components allowed us to identify each gamma emitter. This suggests that, using this method, we can identify and classify gamma radiation emitters present in a sample only on the base of the correlation coefficients.
Figure 3: Intercorrelation between the extracted independent component and recorded observation corresponding to one radioelement. (a) Case of Europium. (b) Case of Sodium. (c) Case of Cadmium.

Acknowledgments. The experiments have been released at the Neutron Activation Analysis Laboratory (NAAL) of the National Centre for Nuclear Energy, Sciences and Techniques (CNESTEN). We are grateful to Dr. Hamid Bounouira for his great cooperation, pertinent remarks and insightful discussions.

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Received: August 15, 2014; Published: December 3, 2014