Review on Comparison of Automated Isotope Identification Algorithms for NaI(Tl) Spectrometer

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Abstract **- There are different algorithms for isotope identification in Gamma ray spectra. Previous research applying machine learning algorithms to isotope identification is promising. The algorithm should be able to perform well on spectra contains a mixture of isotopes. Spectral features are difficult to analyze in case of low-resolution detectors. It becomes hard to identify when features overlap.**
In this work, attempt made in comparison of all existing algorithms, their performance for isotope identification and issues related to each and every algorithm.

INTRODUCTION

There are many challenges for isotope identification algorithms to overcome. The detection phenomena is intrinsic to the detector, an effect of the interaction of radiation with matter and nature of radiation sources. Sodium iodide crystal activated with thallium (NaI(Tl)) coupled with photo multiplier tube and multi-channel analyzer is the instrument used to identify and detect radioactive isotopes and their concentration in various materials meant for environmental, atomic mineral exploration and forensic applications. Sodium iodide Spectrometer is low cost and highly efficient over other largely used detectors like high purity germanium detectors (HPGe) there are several limitations for automated isotope identification algorithms.

1. Due to poor energy resolution of NaI spectrometers, it is not possible to resolve many of the photo peaks in a spectrum.
2. NaI spectrometers are sensitive to temperature changes, as the temperature alters, the energy calibration will change, and the position of peak will shift significantly. It leads to incorrect identifications [1].
3. There is an amount of unknown radiation from cosmic sources and background radiation from naturally occurring radioactive material. Few methods remove the background measurement from source measurement.

Finally, a common issue for all methods is that attenuating materials reduce the count of gamma rays, that reach the detector, making counting statistics poorer and photo peaks are worse to resolve.

Once a spectrum has been measured, there are many methods to perform isotope identification. In this paper it was discussed the overview of all different algorithms and their performance in isotope identification. Most of the methods are passive isotope identification methods classified as following categories[2]

1. Library comparison
2. Region of interest
3. Template matching
4. PCA
5. Neural Network approaches

Methods of isotope identification in a gamma ray spectrum are library comparison, region of interest (ROI), eigenvector methods, template matching, neural network approaches and expert interaction methods.

1. Library Comparison Algorithms:

Library comparison method also called as peak matching method. In this method the algorithm compares the measured peak energies with the library isotope energy peak data. This method is simple among all the identification algorithms. It involves in accurate peak localization and extraction from spectrum. But its performance gets deteriorated in the events of poor detector calibrations and shift in gains in the applications for NaI (Tl) crystal detectors. The method compares the measured peak energies in the data against an isotope library, poor detector

calibrations and gain shifts degrade its performance. it is also completely depending on accurate peak extraction from a spectrum [7]

There will be a discrepancy between measured and library peaks. Poor counting statistics will cause missed peaks or errors in the peak fitting. This algorithm fails often for many reasons. For example, identifies few complex isotopes even though the spectrum contains simple isotopes and when analyzing the low-resolution spectra, the presence of multiple isotopes will distort peaks nonlinearly. The logarithm gives an identification of 'Unknown isotope' when the ratio of the required portion and unnecessary portion of spectra crosses a threshold [3,4].

ROI REGION OF INTEREST ALGORITHM

This approach of analyzing the spectrum involves the comparison of elevated counts in small portion of unknown spectrum with the counts in corresponding portion of known standard spectrum. Very few number of non- overlapping ROI are possible in a gamma ray spectrum will be available for analysis. The overlapping peaks in the form of ROIs in NaI detector limits the usage to few number of isotopes. For example, this algorithm gets confuse to distinguish 228Ac of thorium series (major gamma peaks at 911 KeV and 969 KeV) and 234Pa of uranium series [7]

Convolution and deconvolution methods: Decomposition and deconvolution methods used to simplify the decisions of the spectra. hence identification of peaks preprocessing will become easier. The collected output spectrum S(E) If the convolution form of incident spectrum J(E) and the detector response function R(E,E0) [5].

$$S(E) = \int \infty R(E;E0) - I(E0)dE0$$

The aim is to deconvolve the above equation to find the attributes of incident spectrum I(E). there are different methods to do they job, such as linear regularization, maximum likelihood estimation using expectation maximization (ML-EM), or maximum entropy method (MEM) etc. In each of these methods, the detector response R(E0) will be measured directly, then the

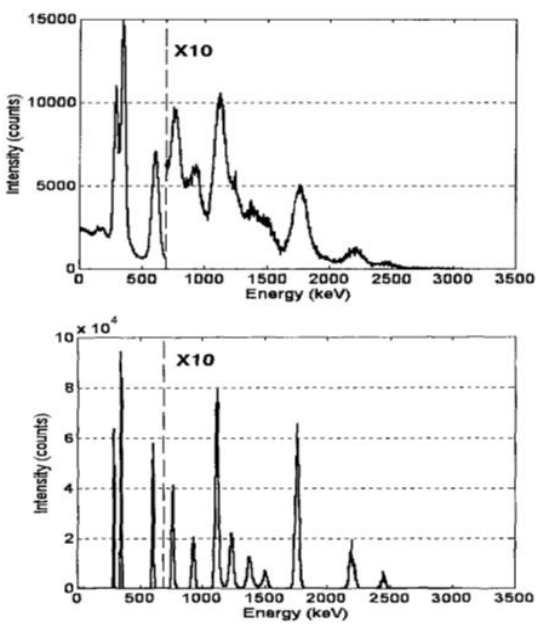

Fig:1An example of ML-EM deconvolution (bottom) using a simulated spectrum (top)[8].

Principal component analysis (PCA): This method involves in finding a new set of basis vectors for the input data set. The fisher discriminant analysis also works on this similar line.

The new data matrix y= PTX,X is the matrix of large data set of spectra. PT is rotation matrix.to bring the data matrix along the maximum variation. The rotation matrix PT is selected such that the covariance matrix of Y is diagonal. The eigen values of of P can be selected under some threshold to reject and get smoothed data which will reduce dimensionality of the input spectral data set[6].

A discriminating function will be applied to separate different classes. Mahalano by distance, the distance from each cluster separation will be computed. In ideal cases these classes will be well separated. But in the case of low resolution NaI spectra it is not well separated.

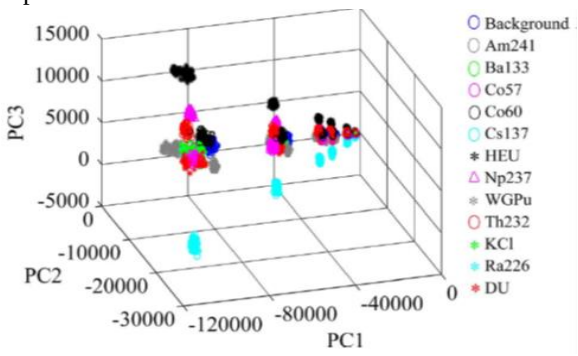

Fig 2: An example of PCA is shown in the following[10]

PCA applied to a large set of spectra, with the first three primary components used for clustering. Some clusters are easily separated, while others (such as DU) are not[9].

TEMPLATE MATCHING METHODS

Template matching method is well established method for identifying isotopes in low resolution gamma spectroscopy. A big set of library spectra (either recorded or simulated) for many isotopes and their geometrics. For each of unknown spectra and library template, the mahalanobies distance or X2 test will be calculated as an error. This method minimizes the effect of poor calibrations and drifts in gain[11].
In this method the whole spectrum will be used at one go. The geometry of the source and detector assembly also can find by analysis vast library datasets and their continue.

NEURAL NETWORK APPROACHES

Artificial neural networks (ANN) are a type of mathematical methods developed on the analogy of neurons [12]. Though there are many classes of machine learning algorithms are available, the ANNS are more popular in identification of isotopes, because of their simplicity in method of teaching the algorithm, and availability of ample published literature.
ANN's are available in many classes including simple feed forward networks [13,14],abductive neural networks[18],convolutional neural networks[17] and radial bias function neural networks. Many demonstrations in literature followed these methods in the problems of isotope identification[19],activity estimation [18,15] and peak fitting. The feed forward networks are more suitable in isotope identification in the case of low-resolution detector like NaI(tl).
A feed forward neural network is constituted by the sandwiching few numbers of hidden layers. One hidden layer B shown in fig 3.between input A and output C layers. Every hidden layer consists of many neurons like B1,B2, …BJ. These neurons will be activated by getting the weighted sum of the previous layer output through an activation function. Sigmoid function is one such function ,which can be described as f(t)=1/1+e-t. the depiction of activation is clearly shown in fig 4.

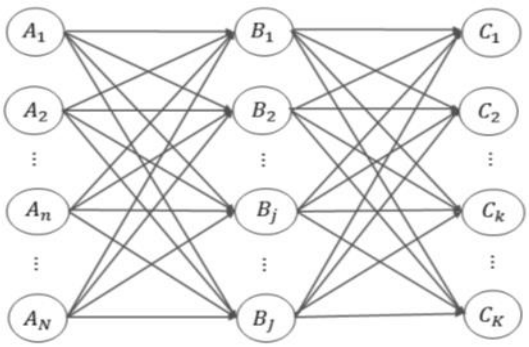

Fig 3 :A representation of a two-layer feed forward neural network

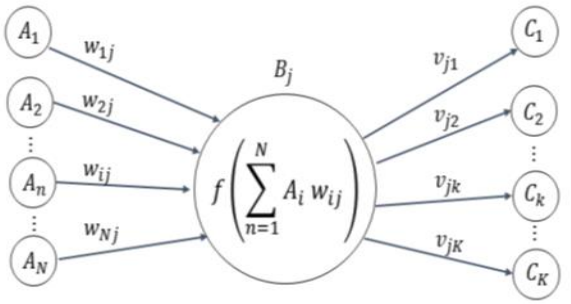

Fig 4 :A representation of the operation of a single neuron Bj

Many authors used the HpGe detector and its spectra to teach the feedforward neural network . HpGe has a significantly better resolution, but the operation is cumbersome as well as costlier affair compared to NaI. Very few authors used [18,19,20] used NaI detectors to train the ANN algorithms.
And few more effective challenges can be discussed in detail later.
A part of spectrum of NaI or a channel information of energy and concentrations will be used to train the algorithm. Even PCA (principle component analysis) smoothed spectrum which has less dimensionality also can be used to train the algorithm.

CONCLUSION

Gamma Ray spectrometry is a physical method of analyzing the spectra generated from various materials of interest like environmental, geological includes uranium exploration, forensic etc. studies. Analysis of such spectra requires vigorous expert interaction to

draw the qualitative and quantitative information. The advent of above discussed identification algorithms and machine learning applications helps the analyst effectively in the cases like high throughput of samples, identifying isotopes with low resolution detectors, identifying nuclides in moving radio nuclides etc.

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