

**MINDS ADVANCED ALGORITHMS FOR RESOLVING GAMMA-RAY SPECTRA**

**Premise:**

The differences in performance characteristics of sodium iodide (NaI) versus Germanium for gamma-ray spectroscopy are well characterized. However, the increased resolution of germanium detectors, obvious upon visual inspection of the spectra, can be illusive when evaluating the advantages for algorithms that automatically identify radionuclides within spectra. Many gamma spectroscopy-based sensors have and will be deployed as standalone, automated surveillance/detection systems, a reality that places the performance and reliability of automatic radionuclide identification algorithms at central and increasing importance. It is our premise that the tradeoffs in cost and complexity between higher-resolution detectors and new algorithms to reliably resolve complex, “noisy” spectral data favor the latter.

**Hypothesis:**

Traditional automated peak-fitting algorithms for identifying radionuclides in gamma-ray spectra work much like the human eye in determining specific radionuclides. When employing these conventional tools, nuclear spectroscopy data derived from scintillators may prove to be indeterminate as to the identification of originating specie. The problem of identifying embedded spectra, while difficult for the unaided eye and corollary conventional algorithms, is subject to acceptable resolution when it is addressed with more sophisticated algorithms.

**Characteristics of NaI Scintillation Hardware:**

As compared to other detection technologies, robust, highly sensitive NaI crystals are available at relatively low cost. No refrigeration of the scintillating material is necessary, as is the case for semiconductor (Germanium-based) detectors. This allows the fabrication of relatively low-cost, highly sensitive NaI detectors which are robust to a wide range of real-world environmental operating conditions.

Sophisticated algorithms such as those used in MINDS bring to fruition the true potential for hyper-accurate, cost-effective NaI-based nuclear detection technologies.

**MINDS use of Artificial Intelligence Algorithms:**

The essential concept in this innovative application of computer algorithms to automated radionuclide identification is the result of a shift in the perception of the task of spectroscopy. The problem can no longer be perceived as merely the identification of an idealized set of isolated peaks in the gamma-ray spectrum of a specific radionuclide. Rather, the characteristic signal produced by a certain scintillating detection apparatus in the presence of a specific radionuclide, including noise and scattering, specifies an overall spectrum pattern that is unique in its own right. This recasting of the problem

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highlights the role that artificial intelligence (AI) algorithms play in its resolution; the very goal of AI is, in fact, hyper-accurate pattern recognition.

Artificial intelligence codes consist of two distinct algorithms: the “training” algorithm and the “classification” algorithm. The training algorithm is fed with a large number of multi-dimensional data samples (in the MINDS case, gamma-ray spectra), which have been pre-labeled with the desired binary classification. In the case of MINDS this labeling signifies whether a specific radionuclide in the detection library is present or absent.

The training algorithm then analyzes this data to “learn” the most efficient and reliable rule for distinguishing positive from negative examples. The output of the training algorithm is a small, efficient classification algorithm that is used to classify input samples (spectra) in real-time.

The application of this methodology to the radionuclide identification problem is straightforward:

- (1) Train one binary classifier for each radionuclide in a desired library, using a large set of sample spectra that are labeled with the presence or absence of that radionuclide’s signature. These spectra should represent a sufficient array of signal strengths, background noise levels, and combinations of the presence and absence of other radionuclides.
- (2) After a classifier is trained for each of the library elements real-time identification of each spectrum from a gamma sensor is obtained by evaluating the classifier for each radionuclide in the library.
- (3) The efficiency of the classification algorithm is such that a single spectrum can be tested, using generic computing hardware, against a large library of radionuclides in a fraction of a second.
- (4) In this way the presence or absence of any combination of library-resident radionuclides in the spectral record, whether embedded or not, can be determined.

This approach capitalizes on the fact that artificial intelligence algorithms do not ‘see’ spectral data in the same way as does the human eye, or its corollary conventional peak-fitting algorithms. It has been demonstrated that artificial intelligence algorithms are capable of analyzing the data with sufficient acuity as to render the increased resolution of germanium detectors unnecessary for many applications. It has also been demonstrated that AI is fully capable of dealing with the problem in which a certain radionuclide’s peaks may be masked by peaks of other nuclides in the same energy range. In what would be a very difficult judgment call for the human eye or its software corollary, the “classifier” trained using artificial intelligence automatically selects and weights the most significant global features of the spectra to enable accurate identification of all library-present radionuclides.

The nature of the feature selection and weighting done within the context of the AI systems incorporated in MINDS can be illustrated by considering one artificial

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intelligence framework in particular, Support-Vector Machines (SVMs), as invented by Vladimir Vapnik [1].

Support-vector machine training algorithms comprise a geometric framework, in that they define a way to partition the high-dimensional space of training samples using a hyperplane that provides the widest ‘margin’ between the positive and negative samples. By doing so, SVM training algorithms effectively search for the features of the input space that differentiate the positive from negative examples by the widest margin, thereby discovering the important or essential dimensions that differentiate the two categories of samples. For example, if a gamma-ray spectrum consists of 1024 integer data points, corresponding to energy levels, the SVM training procedure for a particular radionuclide would examine a set of points occupying 1024-dimensional space, each point consisting of one spectrum in the training set. This procedure converges to a hyperplane that optimally “slices” the 1024-dimensional space of spectra into two halves with all positive samples on one side and all negative examples on the other. In the more difficult case where a perfect separation is not possible, the training algorithm works to minimize the weighted error of samples that are placed on the side of the hyperplane opposite to their true classification.

After training is completed, any future spectra can be classified in real-time by the mathematically straightforward operation of determining on which side of the trained hyperplane the spectra falls.

In this way, the training algorithm in the MINDS code finds precisely those spectral features that indicate the presence of the designated library-resident radionuclide and, on the negative side, learns to screen out ‘deceptive’ features found in other radionuclides, e.g. radionuclides with peaks in the same region. Features not noticeable to the human eye or its (peak-fitting) software corollary, such as a series of small variations in relative peak strengths, become obvious to the trained support-vector machine. Even when the spectra of two distinct radionuclides have a peak in the same energy band, the support-vector training algorithm is capable of finding and identifying features in its representation that separate them by a great distance, resulting in accurate and empirically verifiable identification.

The inherent capability of the AI systems adopted in MINDS can and has been enhanced by normalization techniques, as well as by projecting the data into a higher-dimensional feature space that accentuates the desired distinguishing features. Furthermore, in MINDS the AI is coupled with a second, traditional peak-fitting algorithm, run in parallel. Heuristic decision logic is employed to compare the results of the two independent algorithms, producing an ever higher level of classification accuracy.

### **Examples of AI Discrimination and Identification:**

In this section we present two examples of the capability of MINDS AI codes to identify radionuclides with overlapping or hidden peaks.

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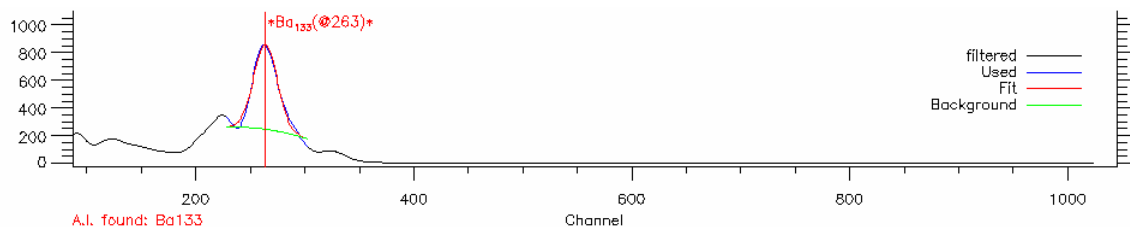
The isotopes Barium-133 and Iodine-131 provide an example of two common radionuclides that have energy peaks near each other in the gamma-ray spectrum, with peaks at energies 302.8 and 284.3 keV, respectively. The average peak width for these elements using a NaI crystal is approximately 40 keV. The spatial distance between these two peaks is small enough that they may not be distinguishable to peak-fitting algorithms or to the unaided human eye. Furthermore, when Ba-133 and I-131 are both present, in the gamma-ray spectrum only one distinct peak may be visible.

However, we have analyzed the spectra employing our Support Vector Machine (SVM) artificial intelligence algorithms and found them able to automatically compensate for these similarities and produce a highly efficient procedure to distinguish between Ba-133 and I-131.

In this case two SVM classifiers were trained separately, one for Ba-133 and one for I-131, using training data sets consisting of spectra synthesized for each of the two radionuclides at various intensity levels, using the characteristics of a NaI detector. Then, for testing purposes, additional spectra were generated for each element at different intensities than the training spectra.

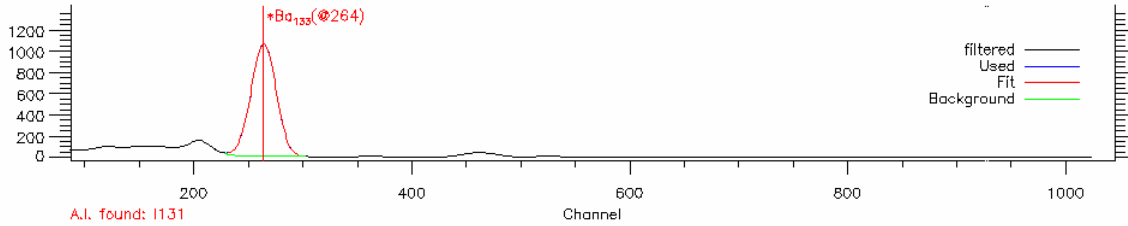
There are more significant differences between the spectra of Ba-133 and I-131 in the lower-energy channels, especially below 152 keV. But in order to more stringently test the capabilities of the AI algorithm, as well as to more closely model the real-world situation of greater background noise in the lower channels. The spectra used in training and testing have been "thresholded" such that no energies below 152 keV are considered—thus eliminating other distinguishing features and making the analysis in this example considerably more difficult.

Figure 1 and Figure 2 depict the graphs of two independently generated test spectra for Ba-133 and I-131, with the results of both the peak-fitting and artificial intelligence algorithms labeled on the graph:



**Figure 1** Barium-133 identified successfully

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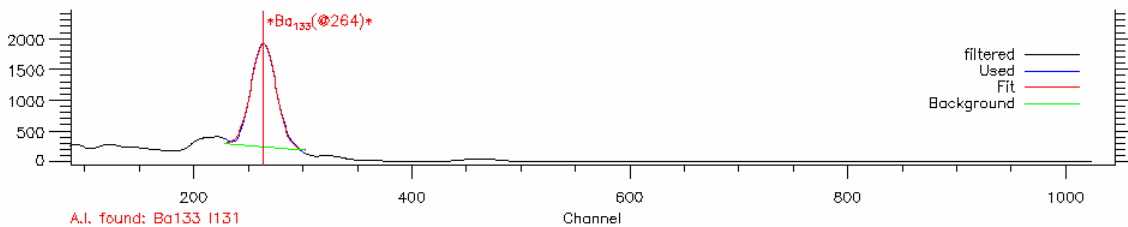


**Figure 2** Iodine-131 found; peak-fitting gives a false result

The result of the artificial intelligence algorithms is displayed in the text below the graph. The peak-fitting result is shown by the vertical line through the center of the peak with the label at the top. Even though the actual element present is I-131, the peak-fitting algorithm has here been instructed to locate Ba-133 in this energy band and has no means to avoid a false identification.

Conversely, the SVM classifier correctly identifies the radionuclides in both cases. Note that the SVM algorithms first normalize the data that they process; therefore they discriminate using relative peak heights and do not depend upon absolute intensity. Through the SVM training procedure, the code has automatically “learned” to search for the subtler features that differentiate the spectra of the two radionuclides.

As a final test, a spectrum was constructed that contained the signatures Ba-133 and I-131, present at similar levels of strength:



**Figure 3** Embedded Ba-133 and I-131 both found.

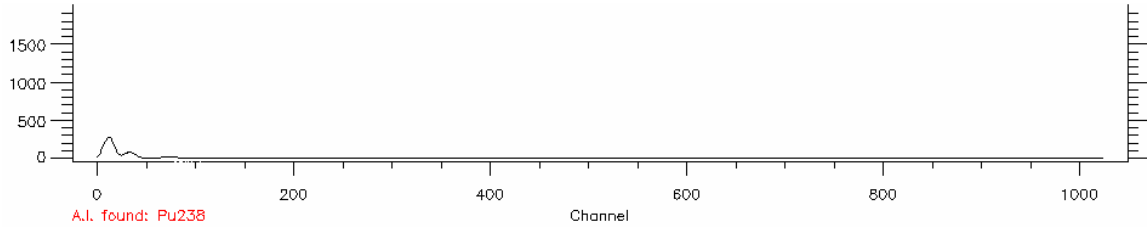
As Figure 3 shows, using the SVM algorithms both radionuclides are successfully found, though to the human eye it is extremely difficult to tell which of the two elements are present. The classifiers for Ba-133 and I-131 were **not** trained on any spectra containing a combination of radionuclides. Nevertheless, they have learned the features that distinguish Ba-133 and I-131 to a level that both classifiers can consistently recognize their respective element’s signature within the combination spectrum.

As a second, more difficult example, we consider the case where a radionuclide of low intensity has its spectrum peaks almost entirely “buried” by the presence of other radionuclides. This could happen if it were attempted to disguise the presence of a radionuclide classified as a threat material by the presence of non-threat radionuclides. For this experiment, additional spectra were generated containing Plutonium-238 (Pu-238) in addition to the Ba-133 and I-131 used above. Pu-238 will characteristically produce a gamma-ray spectrum with much smaller peaks than either of the other two radionuclides. In the combination of these elements, the distinguishing features of the Pu-

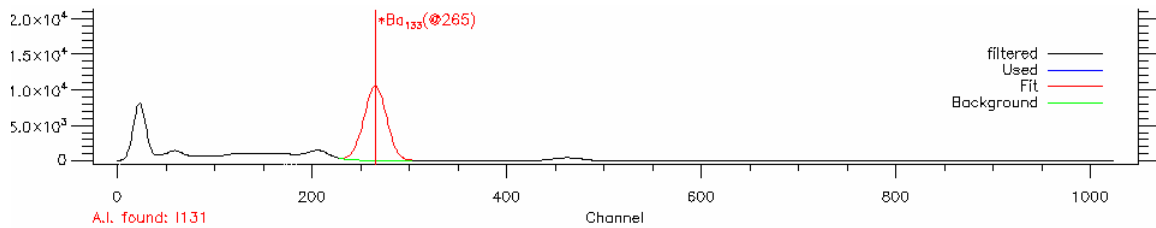
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238 spectra are virtually invisible to the human eye or conventional peak-fitting algorithms.

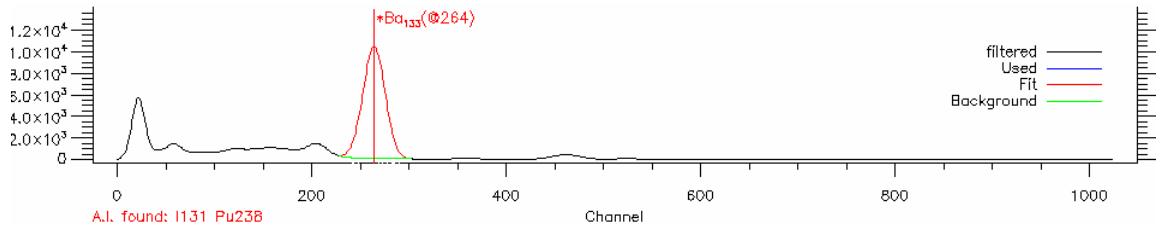
The MINDS code was able to correctly identify the presence of any combination of all three radionuclides in real-time, as shown by the figures:



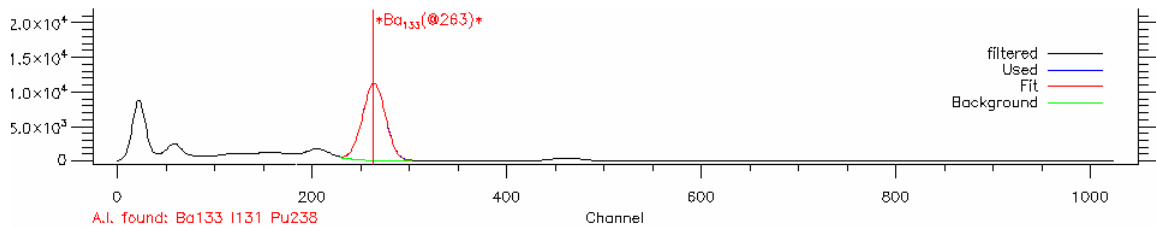
**Figure 4** Plutonium-238 spectra identified.



**Figure 5** Iodine-131 Spectrum identified by AI



**Figure 6** Pu-238 successfully detected embedded in I-131.



**Figure 7** Pu238 found embedded in I-131 and Ba-133

## Conclusion

This work has conclusively and reproducibly demonstrated the advantages of NaI detection technologies when coupled with state-of-the-art identification algorithms. The shift of viewpoint, from considering a gamma-ray spectrum as a set of individual peaks to

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a higher-level view of the pattern produced, was crucial to this advancement. The goal of hyper-accurate, real-time automatic identification of multiple radionuclides can be achieved in a cost-effective manner.

### References

[1] Vapnik, V., *Estimation of Dependences Based on Empirical Data*, Springer-Verlag, 1982.