AUTOMATING SPECTRUM STRIPPING*

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*Based largely on MS Thesis by DiNova entitled "Automated Spectrum Stripping of Photon Spectra"

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TOPICS

- Desired Properties of Spectrum Stripping
- Work to Date
- Lessons Learned to Date
- Future Work

Desired Properties of Spectrum Stripping (SS)

- Background Estimation (or Elimin-ation) in Cases that it cannot be easily obtained
- Quantitative Analysis of Compo-nents that are identified including uncertainties

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WORK TO DATE

- A number of CEAR people have worked on this problem including Dr. Ai, Dr. Johanna Peeples, and Vincent DiNova.
- Vincent did his MS thesis on this and did the job that should have been done many years ago when people were using an iterative visual approach to identify peak disappearance.

LESSONS LEARNED TO DATE

- The Linear Library Least-Squares (LLLS) approach using residuals to approximate any unknown background does not work – no identified relationship has been found between these residuals and the actual background. The residuals obtained are about half positive and half negative. A detailed study of this should be made to determine if a relationship can be found.
- At present one must use a suitable trial-and-error or non-linear LLLS approach for SS (a NLLLS approach) that uses only the highest energy peaks for measuring and subtracting each component library sequentially.

VINCENT DINOVA SS APPROACH

From here, a modified method for using the Spectrum Stripping technique is used, identifying all of the peaks of interest in the problem. This can be carried out by specifying the channel number or energy associated with the beginning and end of a peak of interest. A Chi-Squared analysis is used to find the best fit for that energy peak, using the simulated libraries for the search. This is then subtracted from the entire spectrum and a residual spectrum is output repeating until the contribution of each library is found. It should also be noted that the lower the Chi-Squared value, the better the fit to the data. The equation used to find the Chi-Squared value is shown in equation 3.

VINCENT DINOVA SS APPROACH, 2

Equation 3: Chi-Squared Test

$$\chi^2 = \sum_{i=1}^{n} \frac{(y_{icalc} - y_{iknown})^2}{y_{iknown}}$$

With any method used, errors are often found and should be examined when investigating a researching data. The contribution of each library to the total spectrum has an associated error. The error in the entire spectrum is found to accumulate, leading to a higher error than linear least squares (Guo, 2003). Essentially, the greater number of libraries in the sample, the larger the error will be. This is the major issue with this technique, but it will still be shown to be an effective method.

VINCENT DINOVA SS APPROACH, 3

There are two forms of analysis that can be performed. One, which yields the composition of each of the libraries in the entire spectrum, is similar to using linear least squares, but contains a greater level of error. Another form of analysis is residual identification, residual calculations of the stripped spectrum, used to identify any missing component to the model. After the energy of this residual is determined, a library associated to this energy is added to a linear least squares search, or fitted to the residual spectrum.

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FIRST EXAMPLE

Table 1: Linear Combination of Radioisotopes for Low U-235 Case

Radioisotope	Linear Contribution
Co-60	1.00E+08
Cs-137	1.00E+10
U-235	1.00E+07

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FIRST EXAMPLE, 2

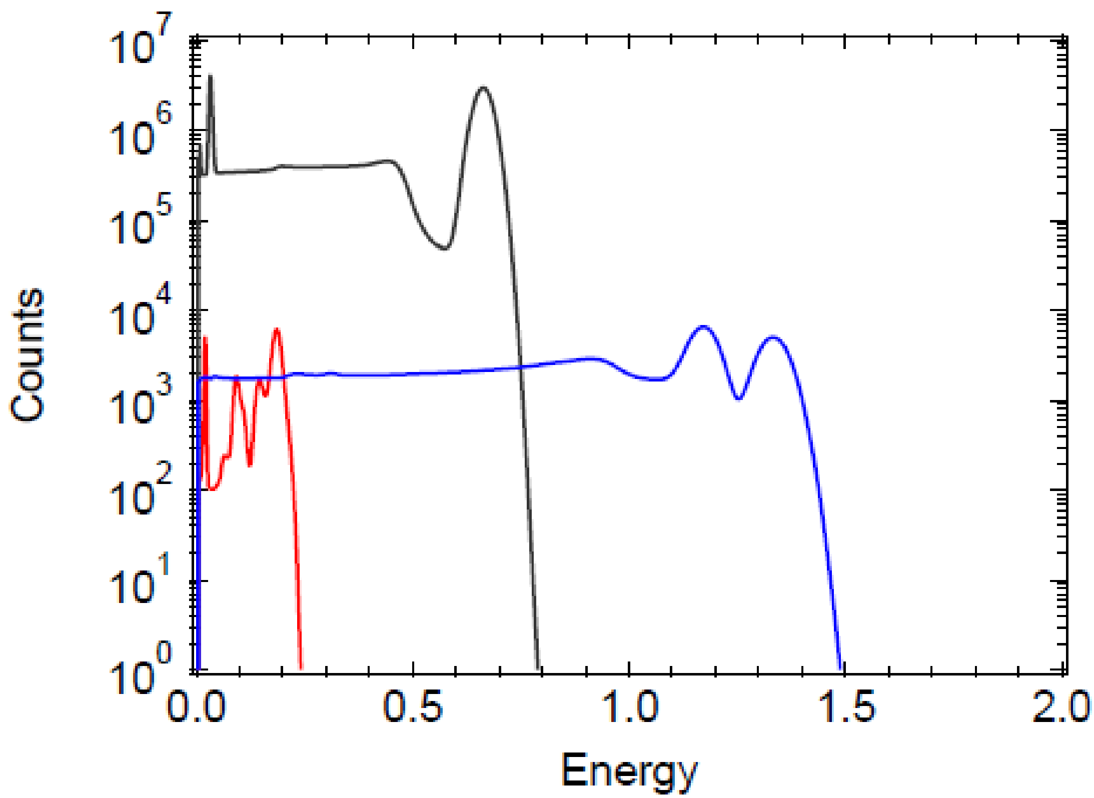


Figure 9: Library Contribution to the Entire Spectrum

FIRST EXAMPLE, 3

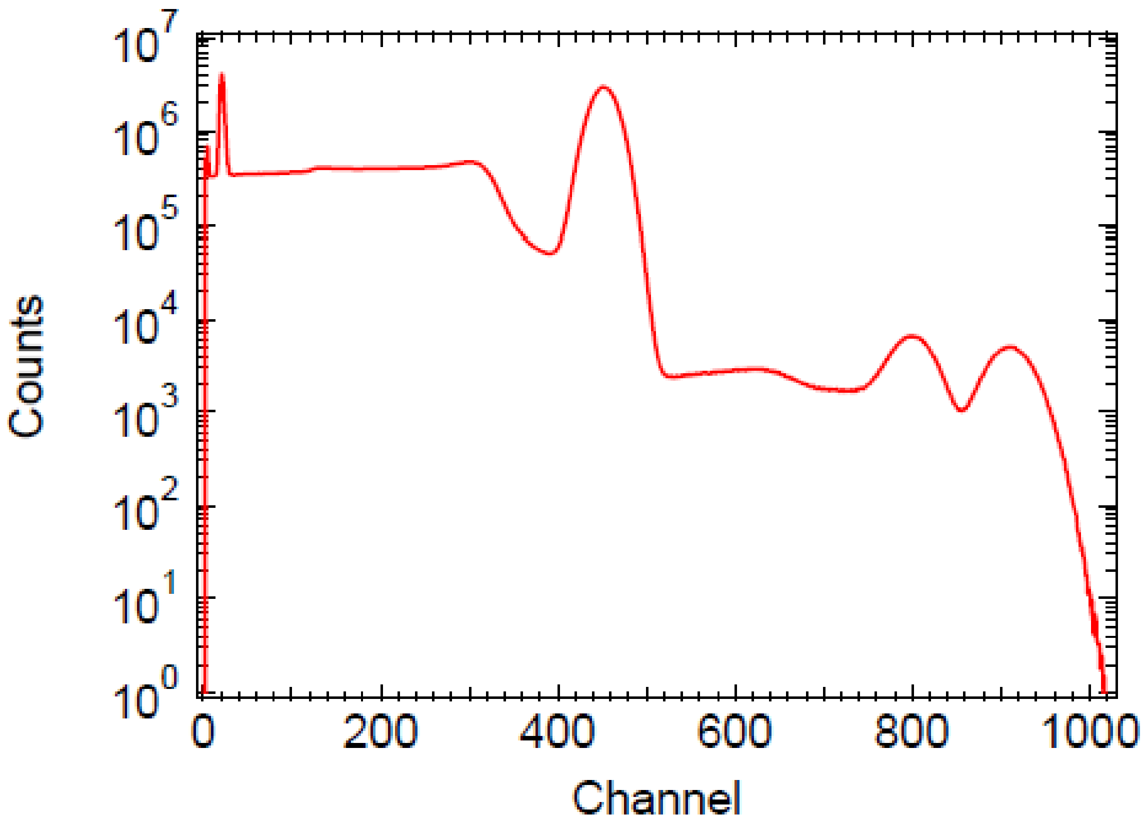


Figure 10: Experimental Spectrum for Limited U-235 Case

FIRST EXAMPLE, 4

After interpreting the data shown in figure 10, the contribution of U-235 cannot be found from visual observation, implying that a screener at a portal monitor would be unable to see any U-235 in this sample.

Next, the libraries for Cs-137 and Co-60 are stripped from the total spectrum. The result is shown as figure 11. This figure shows a close fit to the data from visual observation. The residual calculation reveals that there is a significant difference in the fit as shown in figure 12.

FIRST EXAMPLE, 5

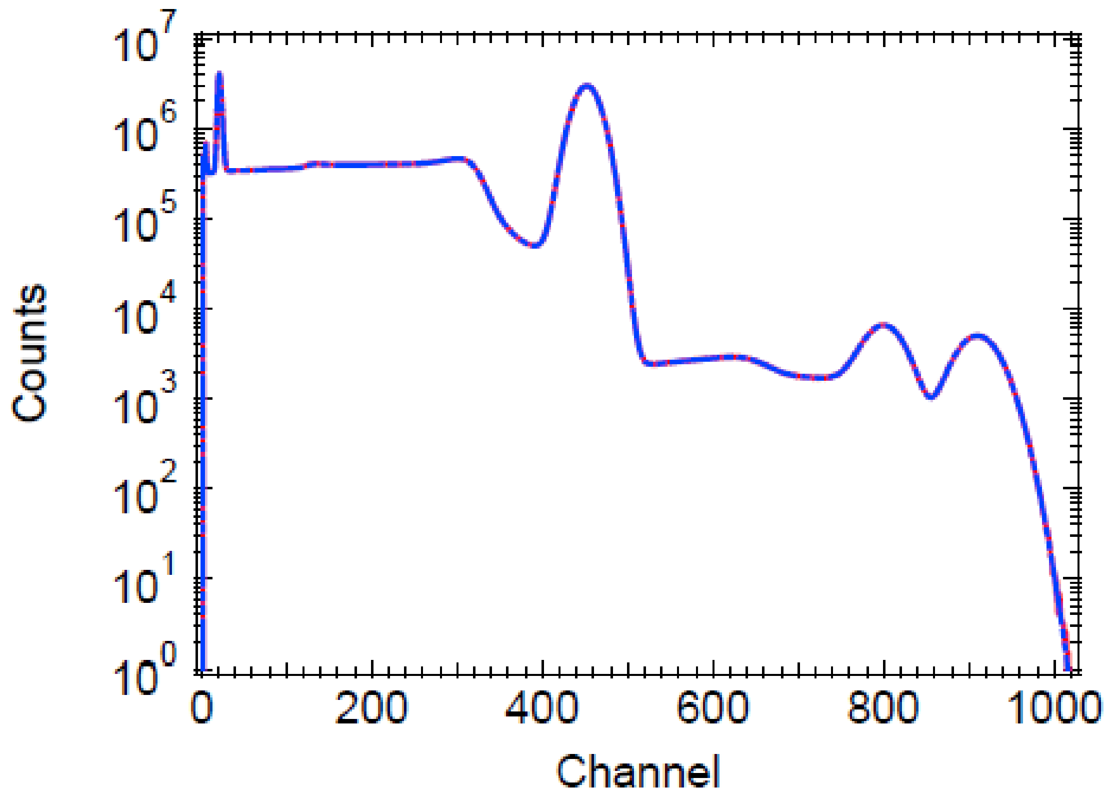


Figure 11: Experimental Spectrum and Fit

FIRST EXAMPLE, 6

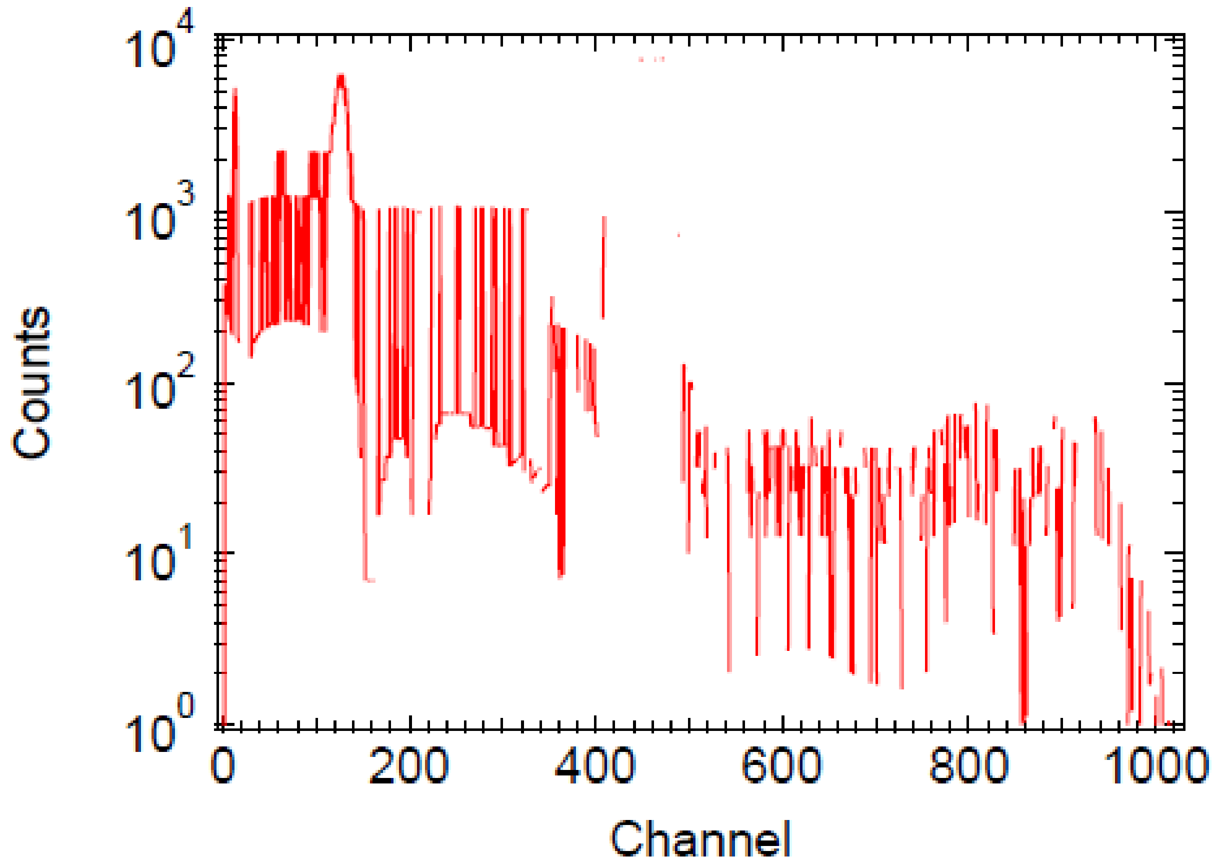


Figure 12: Residuals for Fit

FIRST EXAMPLE, 7

At this point, it is obvious that there is a library missing from the model. After identifying the missing library as U-235, a least squares search can be performed to find the correlation coefficient for U-235. Figure 13 is the best fit for this data.

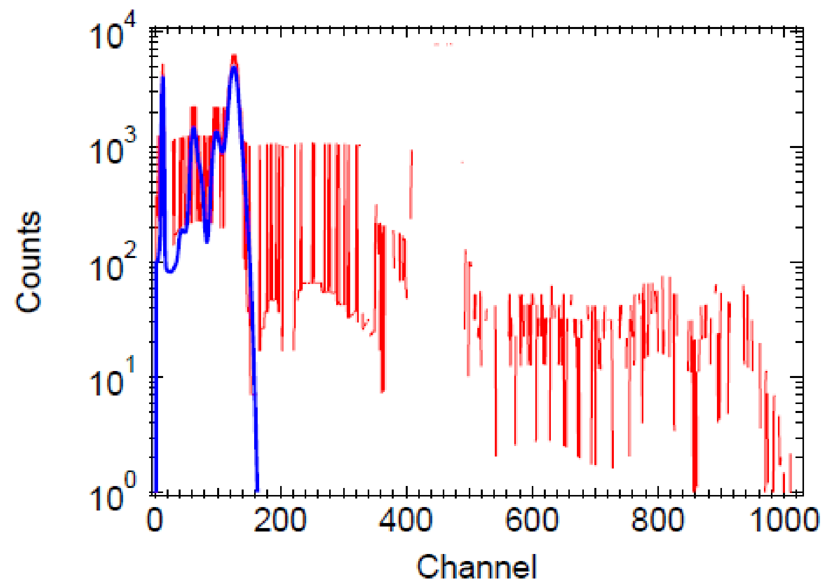


Figure 13: Best Fit for Residual

FIRST EXAMPLE, 8

The calculated linear coefficients by using this technique are shown below in table 2 along with the actual values.

Table 2: Comparison of Results

Radioisotope	Linear Contribution	Calculated Values	Relative Error
Co-60	1.00E+08	9.99E+07	0.07%
Cs-137	1.00E+10	1.00E+10	0.00%
U-235	1.00E+07	7.89E+06	21.06%

FIRST EXAMPLE, 9

This output can be compared to the results that would come from using linear least squares. Figure 14 shows the original data and fit. The result is not visually different from the fit using Spectrum Stripping. Figure 15 shows the residuals, which shows a noticeable difference between these two methods.

FIRST EXAMPLE, 10

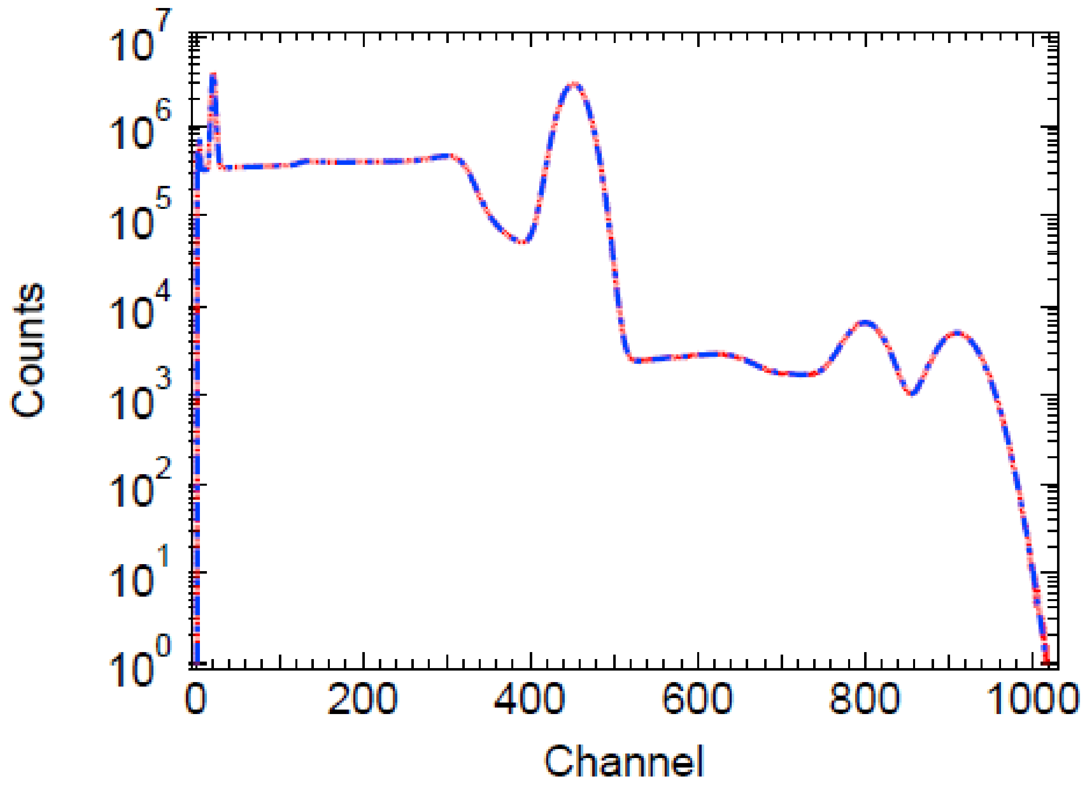


Figure 14: Fit Using Linear Least Squares

FIRST EXAMPLE, 11

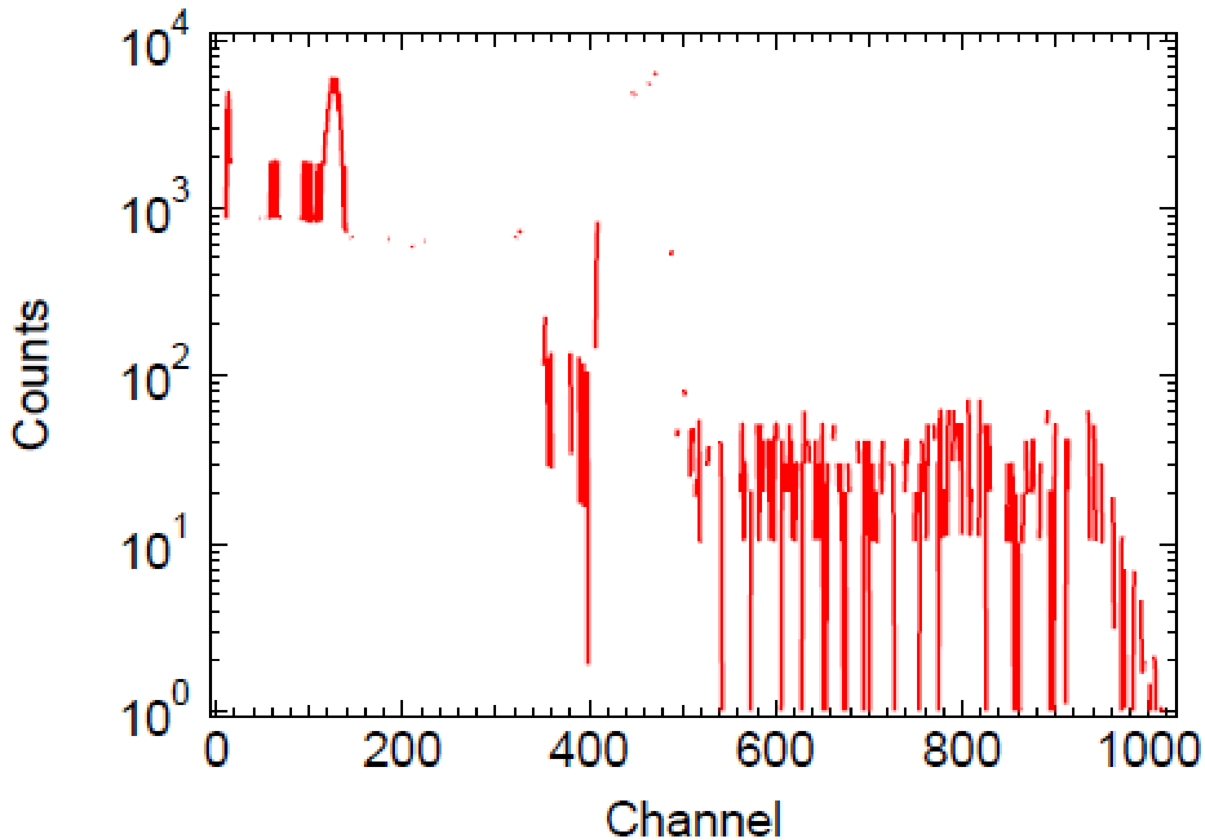


Figure 15: Residuals Using Linear Least Squares Method

FIRST EXAMPLE, 12

The resulting identification a U-235 signature would prove to be difficult, since the peaks are hard to distinguish. This is due to an inherent overshoot that occurs while using linear least squares. This is more apparent in limiting cases such as the low U-235 case. In the case where there is a large amount of U-235, this problem will be less apparent.

The next consideration is the case where there is a large contribution from U-235, using the same analysis from the previous case, Table 3 below lists the new linear coefficients used for this case. The total spectrum is shown as figure 14.

SECOND EXAMPLE

Table 3: Linear Coefficients for High U-235 Case

Radioisotope	Linear Contribution
Co-60	1.00E+08
Cs-137	1.00E+08
U-235	1.00E+10

SECOND EXAMPLE, 2

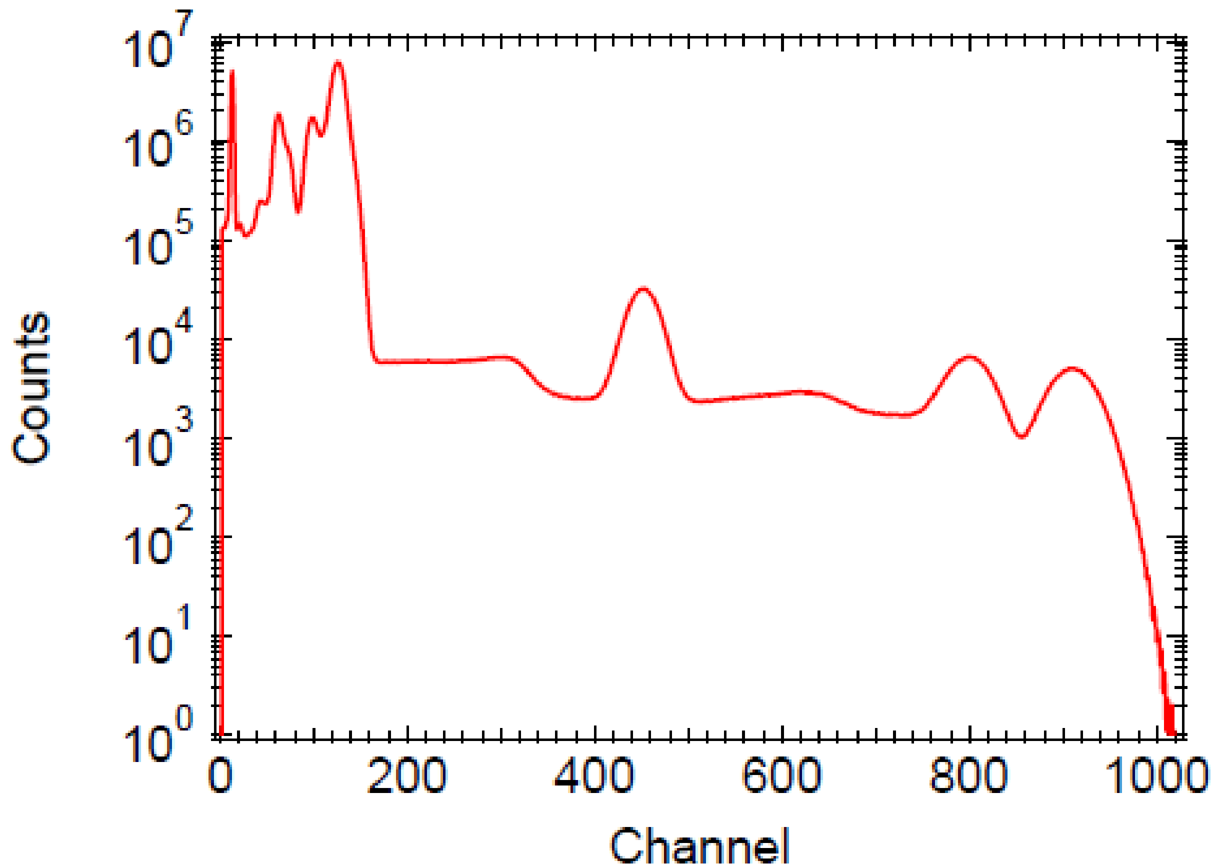


Figure 16: Experimental Spectrum for High U-235 Case

SECOND EXAMPLE, 3

In the same manner as the previous case, the Co-60 and Cs-137 are stripped from the entire spectrum. Figure 15 shows the amount being stripped from the sample. The residual is shown in figure 16 and the best fit is shown in figure 17. The calculated linear coefficients and a comparison to the original data are listed in table 4.

SECOND EXAMPLE, 4

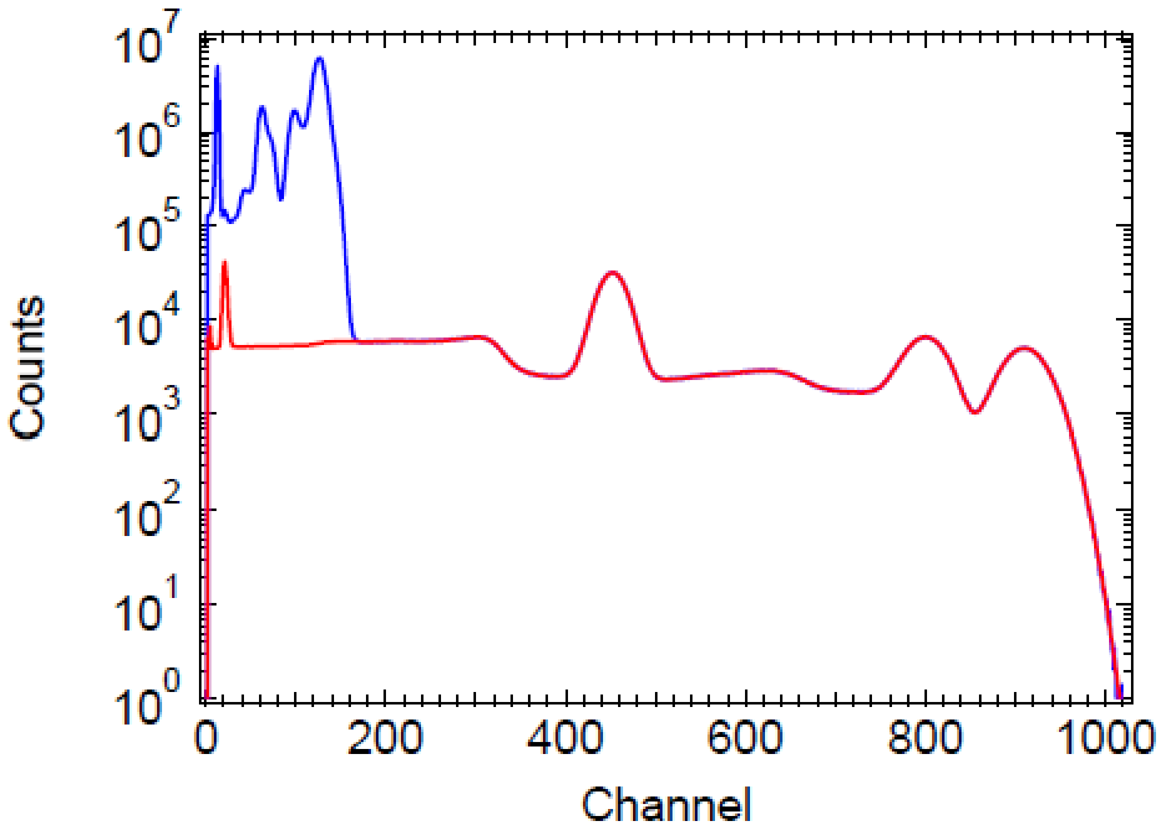


Figure 17: Original Data and Fit for High U-235 Case

SECOND EXAMPLE, 5

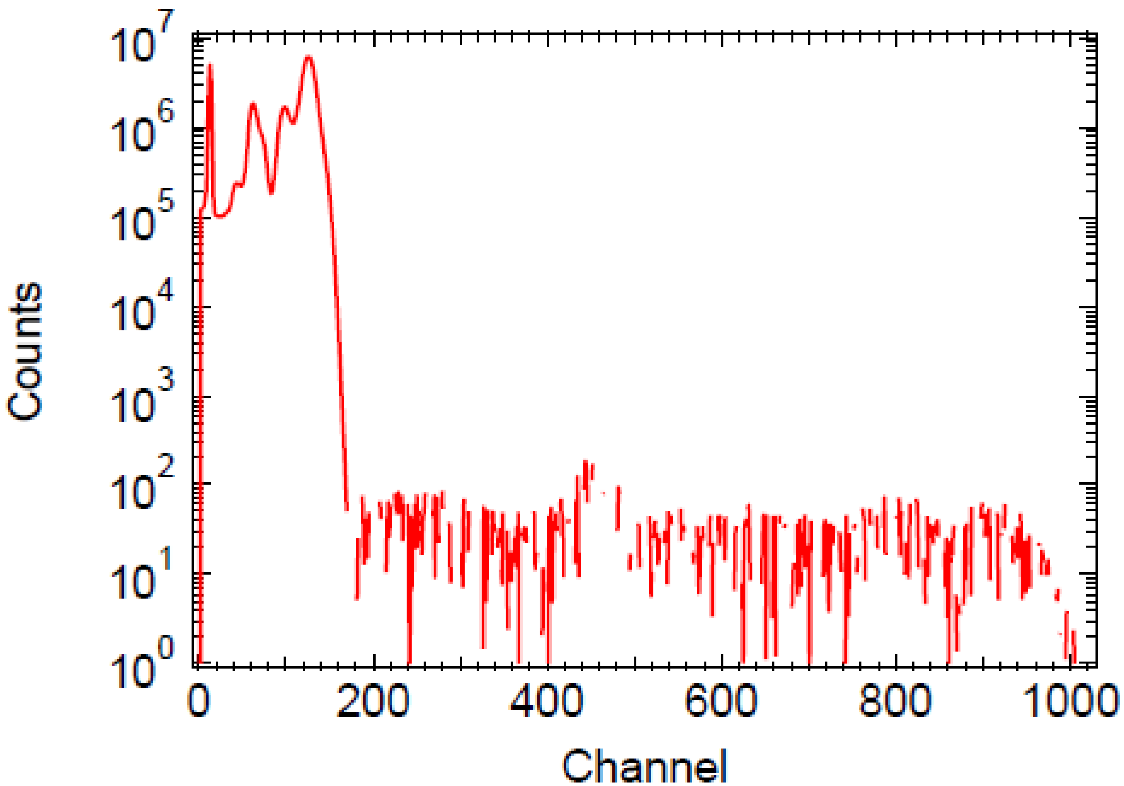
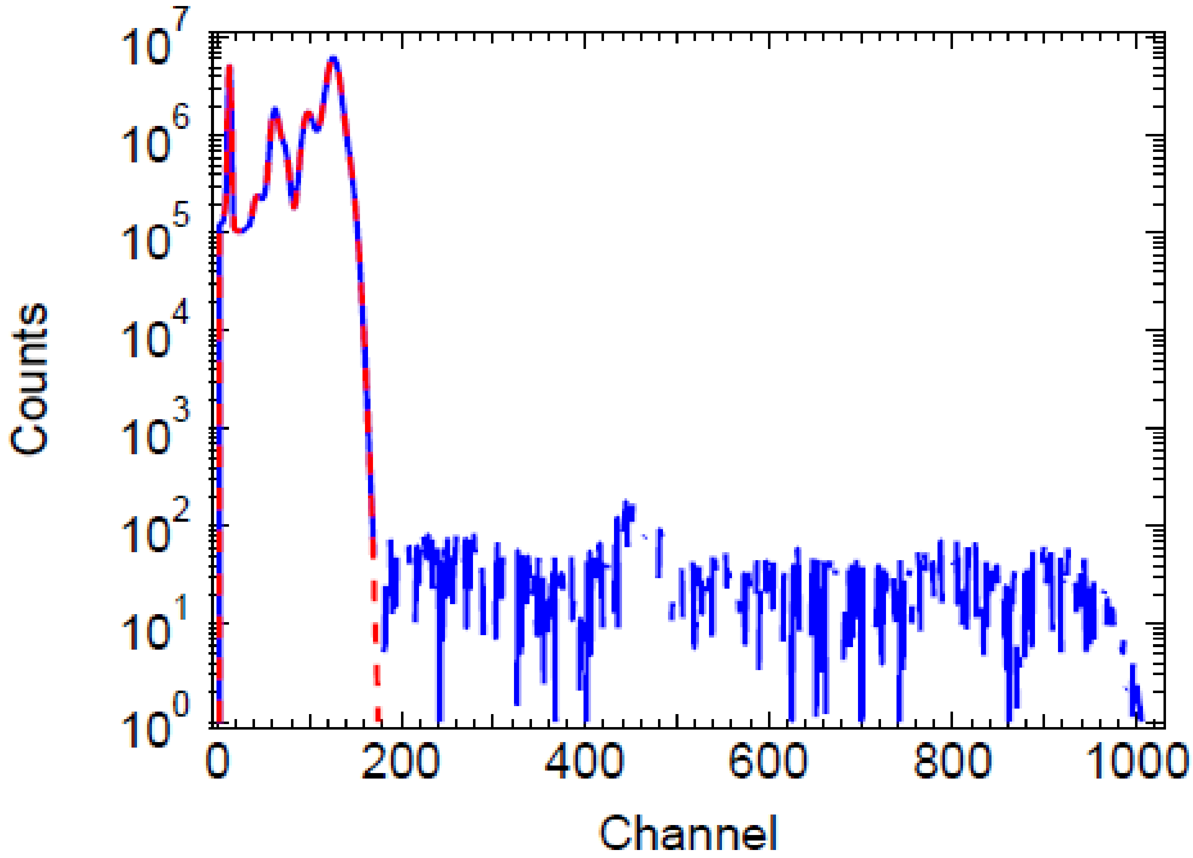


Figure 18: Residual for High U-235 Case

SECOND EXAMPLE, 6



SECOND EXAMPLE, 7

Figure 19: Best Fit for the Residual Calculation

Table 4: Comparison between Experiment and Calculated Values

Radioisotope	Linear Contribution	Calculated Values	Relative Error
Co-60	1.00E+08	9.998E+07	0.02%
Cs-137	1.00E+08	9.997E+07	0.03%
U-235	1.00E+10	9.999E+09	0.01%

FUTURE WORK

- Find a relationship between the LLLS residuals and the true background.
- Determine if a non-linear library least-squares (NLLLS) approach will work.
- Wesley has started his thesis work on this.