Contents

Processing and Visualization Functions			3
1	BA	CKGROUND ELIMINATION	5
	1.1	1-DIMENSIONAL SPECTRA	5
	1.2	2-DIMENSIONAL SPECTRA	8
2	SMOOTHING		21
	2.1	2-DIMENSIONAL SPECTRA	21
3	PEAK SEARCHING		25
	3.1	1-DIMENSIONAL SPECTRA	25
	3.2	2-DIMENSIONAL SPECTRA	30
4	DECONVOLUTION - UNFOLDING		
	4.1	1-DIMENSIONAL SPECTRA	33
	4.2	Gold deconvolution algorithm	33
	4.3	2-DIMENSIONAL SPECTRA	37
5	FITTING		
	5.1	1-DIMENSIONAL SPECTRA	45
	5.2	2-DIMENSIONAL SPECTRA	51
6	TRANSFORMS		
	6.1	1-DIMENSIONAL SPECTRA	57
	6.2	2-DIMENSIONAL SPECTRA	62
7	VISUALIZATION		67
	7.1	1-DIMENSIONAL SPECTRA	67
	7.2	2-DIMENSIONAL SPECTRA	71
References			79

CONTENTS

Processing and Visualization Functions

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CONTENTS

Chapter 1

BACKGROUND ELIMINATION

1.1 1-DIMENSIONAL SPECTRA

This function calculates background spectrum from source spectrum. The result is placed in the vector pointed by spectrum pointer. On successful completion it returns 0. On error it returns pointer to the string describing error.

Function parameters:

- **spectrum** pointer to the vector of source spectrum
- **size** length of spectrum
- number_of_iterations or width of the clipping window

The function allows to separate useless spectrum information (continuous background) from peaks, based on Sensitive Nonlinear Iterative Peak Clipping Algorithm. In fact it represents second order difference filter (-1,2,-1). The basic algorithm is described in detail in [1], [2].

$$v_p(i) = min\left\{v_{p-1}, \frac{[v_{p-1}(i+p) + v_{p-1}(i-p)]}{2}\right\}$$

where p can be changed

- a. from 1 up to a given parameter value w by incrementing it in each iteration step by 1-INCREASING CLIPPING WINDOW
- b. from a given value w by decrementing it in each iteration step by 1- DECREASING CLIPPING WINDOW

An example of the original spectrum and estimated background (INCREASING CLIPPING WINDOW) is given in the Figure 1.1.

One can notice that on the edges of the peaks the estimated background goes under the peaks. An alternative approach is to decrease the clipping window from a given value to the value of one (DECREASING CLIPPING WINDOW). Then the result obtained is given in the Figure 1.2.

The estimated background is smoother. The method does not deform the shape of peaks.

However sometimes the shape of the background is very complicated. The second order filter is insufficient. Let us illustrate such a case in the Figure 1.3. The forth order background estimation filter gives better estimate of complicated background (the clipping window w=10).

4-th order algorithm ignores linear as well as cubic component of the background. In this case the filter is (1,-4,6,-4,1). In general the allowed values for the order of the filter are 2, 4, 6, 8. An example of the same spectrum estimated with the clipping window w=40 and with filters of the orders 2, 4, 6, 8 is given in the Figure 1.4.

Sometimes it is necessary to include also the Compton edges into the estimate of the background. In Figure 1.5 we present the example of the synthetic spectrum with Compton edges. The background was estimated using the 8-th

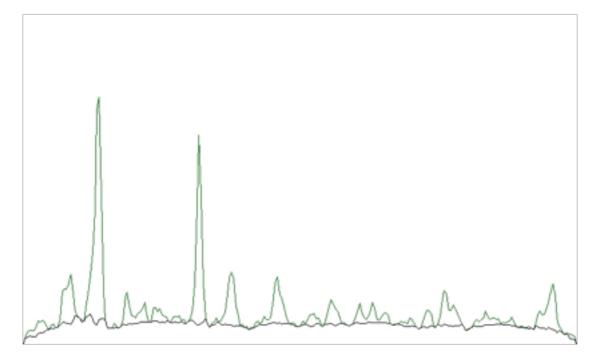


Figure 1.1: Example of the original spectrum and estimated background (INCREASING CLIPPING WINDOW)

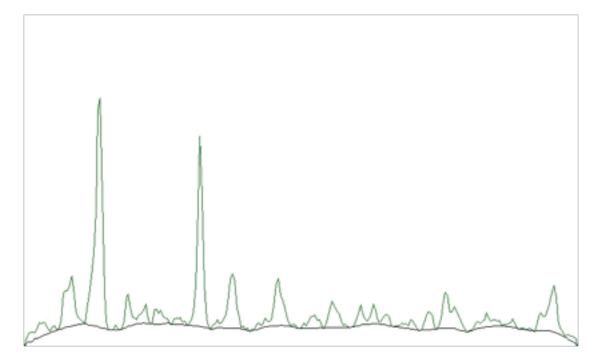


Figure 1.2: An alternative approach is to decrease the clipping window from a given value to the value of one (DECREASING CLIPPING WINDOW)

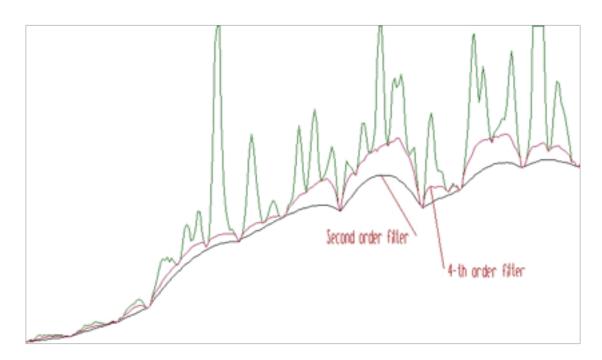


Figure 1.3: The forth order background estimation filter gives better estimate of complicated background

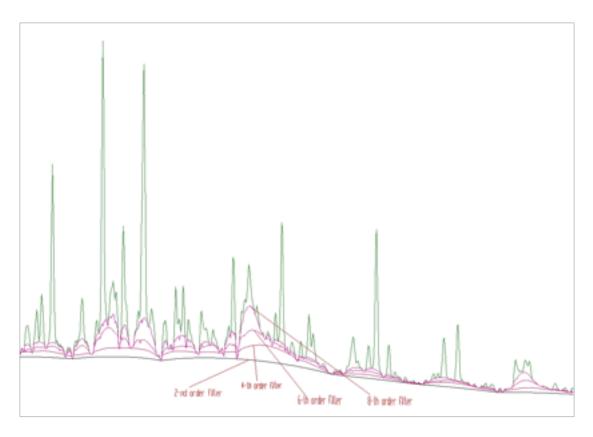


Figure 1.4: The same spectrum estimated with the clipping window w=40 and with filters of the orders 2, 4, 6, 8

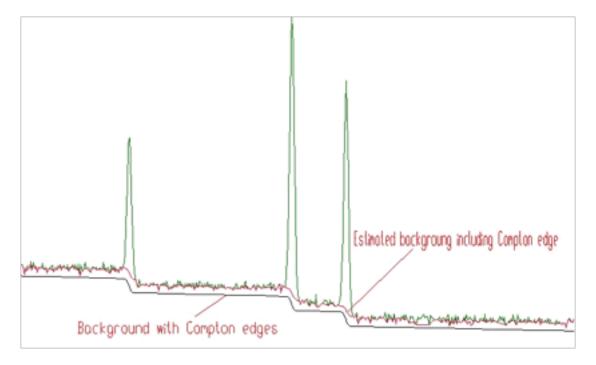


Figure 1.5: Synthetic spectrum with Compton edges

order filter with the estimation of the Compton edges and decreasing clipping window. In the lower part of the Figure we present the background, which was added to the synthetic spectrum. One can observe good coincidence with the estimated background. The method of the estimation of Compton edge is described in detail in [3].

The generalized form of the algorithm is implemented in the function.

The meaning of the parameters is as follows:

- **spectrum** pointer to the vector of source spectrum
- **size** length of spectrum vector
- number_of_iterations maximal width of clipping window,
- direction direction of change of clipping window. Possible values:
 - BACK1_INCREASING_WINDOW
 - BACK1_DECREASING_WINDOW
- filter_order order of clipping filter. Possible values:
 - BACK1 ORDER2
 - BACK1 ORDER4
 - BACK1_ORDER6
 - BACK1_ORDER8
- compton logical variable whether the estimation of Compton edge will be included. Possible values:
 - BACK1 EXCLUDE COMPTON
 - BACK1_INCLUDE_COMPTON

1.2 2-DIMENSIONAL SPECTRA

This basic background estimation function allows to separate useless spectrum information (2D-continuous background and coincidences of peaks with background in both dimensions) from peaks. It calculates background spectrum from

1.2. 2-DIMENSIONAL SPECTRA

source spectrum. The result is placed in the array pointed by spectrum pointer. On successful completion it returns 0. On error it returns pointer to the string describing error.

Function parameters:

- **spectrum** pointer to the array of source spectrum
- **sizex** x length of spectrum
- **sizey** y length of spectrum
- number_of_iterations width of the clipping window

In Figure 1.6 we present an example of 2-dimensional spectrum before background elimination.

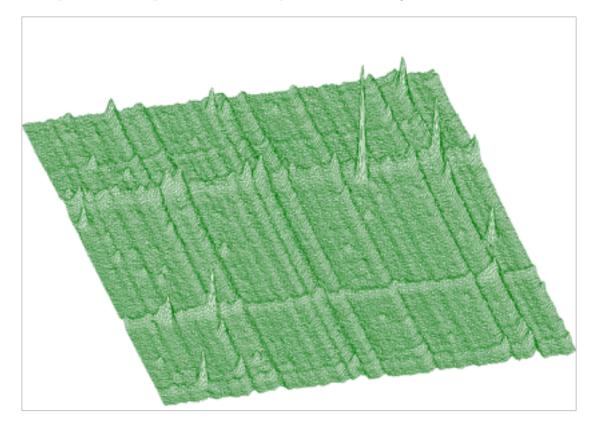


Figure 1.6: 2-dimensional spectrum before background elimination

Estimated background is shown in Figure 1.7. After subtraction we get pure 2-dimensional peaks.

Analogously to 1-dimensional case we have generalized also the function for 2-dimensional background estimation. Sometimes the width of peaks in both dimensions are different. As an example we can introduce n-gamma 2-dimensional spectra. Then it is necessary to set different widths of clipping window in both dimensions. In Figure 1.8 we give an example of such a spectrum.

Spectrum after background estimation (clipping window 10 for x-direction, 20 for y- direction) and subtraction is given in Figure 1.9.

Background estimation can be carried out using the algorithm of successive comparisons [1] or .based on one-step filtering algorithm given by formula:

$$v_{p}(i) = min \left\{ v_{p-1}(i), \frac{ \left[\begin{array}{c} -v_{p-1}(i+p,j+p) + 2 * v_{p-1}(i+p,j) - v_{p-1}(i+p,j-p) \\ +2 * v_{p-1}(i,j+p) + 2 * v_{p-1}(i,j-p) \\ -v_{p-1}(i-p,j+p) + 2 * v_{p-1}(i-p,j) - v_{p-1}(i-p,j-p) \end{array} \right] \right\}$$



Figure 1.7: Estimated background

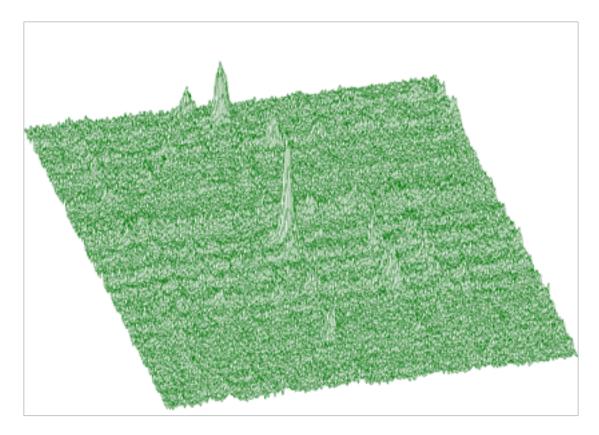


Figure 1.8: It is necessary to set different widths of clipping window in both dimensions

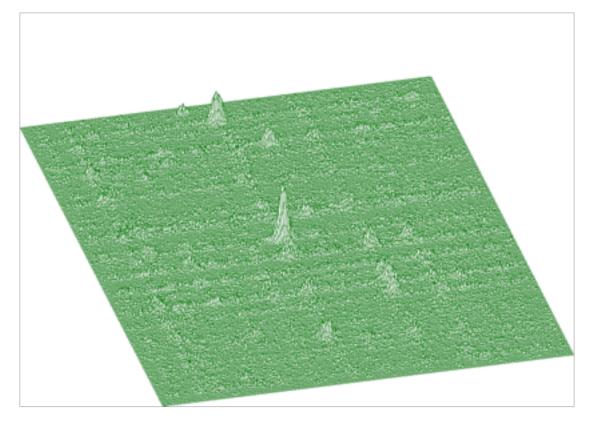


Figure 1.9: Spectrum after background estimation (clipping window 10 for x-direction, 20 for y- direction) and subtraction

Illustrating example is given in the following 3 Figures. In Figure 1.10 we present original (synthetic) 2-dimensional spectrum. In the Figure 1.11. we have spectrum after background elimination using successive comparisons algorithm and in Figure 1.12 after elimination using one-step filtering algorithm.

One can notice artificial ridges in the spectrum in Figure 1.11. In the estimation using filtration algorithm this effect disappears. The general function for estimation of 2-dimensional background with rectangular ridges has the form

char *Background2RectangularRidges(float **spectrum,

```
int sizex,
int sizey,
int number_of_iterations_x,
int number_of_iterations_y,
int direction,
int filter_order,
int filter_type);
```

This function calculates background spectrum from source spectrum. The result is placed to the array pointed by spectrum pointer.

Function parameters:

- **spectrum** pointer to the array of source spectrum
- sizex \boldsymbol{x} length of spectrum
- **sizey** y length of spectrum
- number_of_iterations_x-maximal x width of clipping window
- number_of_iterations_y-maximal y width of clipping window
- direction direction of change of clipping window. Possible values:
 - BACK2 INCREASING WINDOW
 - BACK2_DECREASING_WINDOW
- filter_order-order of clipping filter. Possible values:
 - BACK2_ORDER2 BACK2_ORDER4
 - BACK2_ORDER6 BACK2_ORDER8

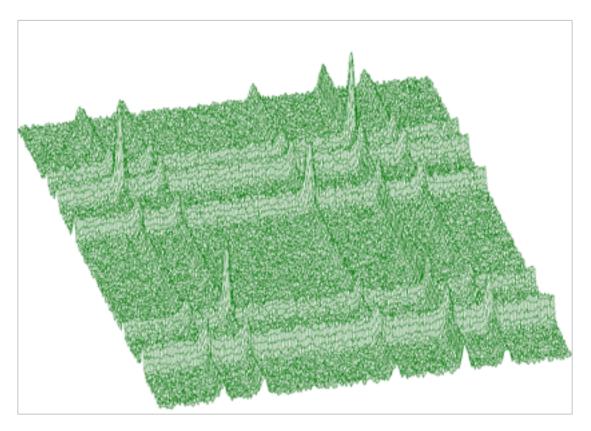


Figure 1.10: Original (synthetic) 2-dimensional spectrum

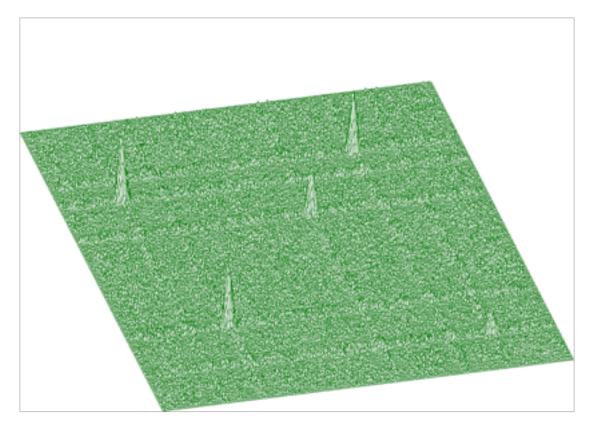


Figure 1.11: Spectrum after background elimination using successive comparisons algorithm

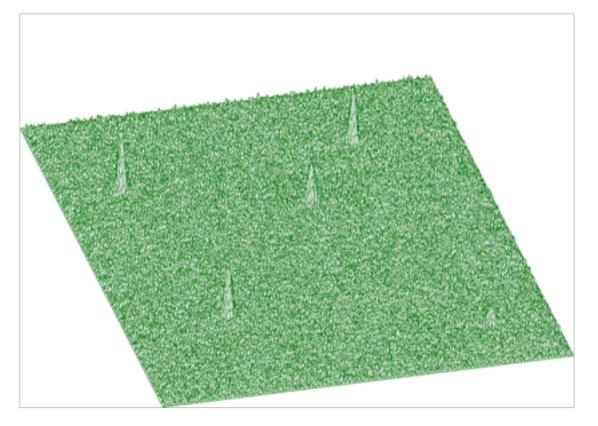


Figure 1.12: Spectrum after elimination using one-step filtering algorithm

- filter_type determines the algorithm of the filtering. Possible values:
 - BACK2_SUCCESSIVE_FILTERING
 - BACK2_ONE_STEP_FILTERING

In what follows we describe a function to estimate continuous 2-dimensional background together with rectangular and skew ridges. In Figure 1.13 we present a spectrum of this type.

The goal is to remove rectangular as well as skew ridges from the spectrum and to leave only 2-dimensional coincidence peaks. After applying background elimination function and subtraction we get the two dimensional peaks presented in Figure 1.14

In Figures 1.15 and 1.16 we present experimental spectrum with skew ridges and estimated background, respectively.

The function for the estimation of background together with skew ridges has the form

char *Background2SkewRidges(float **spectrum,

```
int sizex,
int sizey,
int number_of_iterations_x,
int number_of_iterations_y,
int direction,
int filter_order);
```

The result is placed to the array pointed by spectrum pointer.

Function parameters:

- **spectrum** pointer to the array of source spectrum
- sizex x length of spectrum
- **sizey** y length of spectrum
- number_of_iterations_x maximal x width of clipping window
- number_of_iterations_y maximal y width of clipping window
- direction direction of change of clipping window. Possible values:

- BACK2_INCREASING_WINDOW

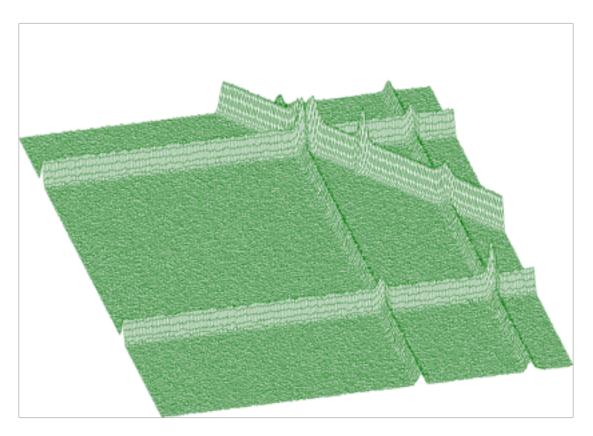


Figure 1.13: Function to estimate continuous 2-dimensional background together with rectangular and skew ridges

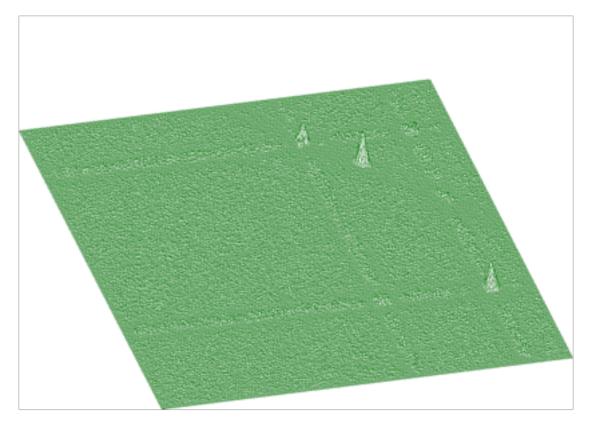


Figure 1.14: Two dimensional peaks obtained after applying background elimination function and subtraction

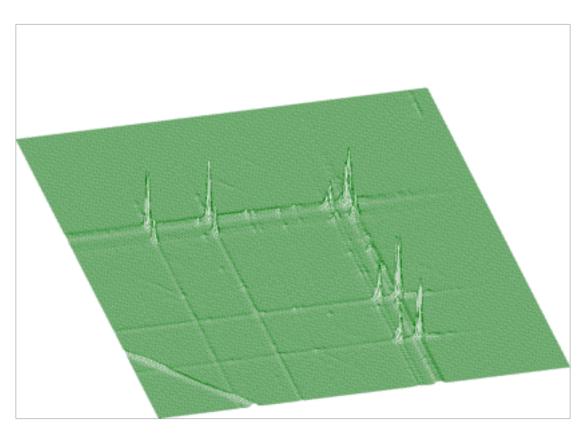


Figure 1.15: Experimental spectrum with skew ridges

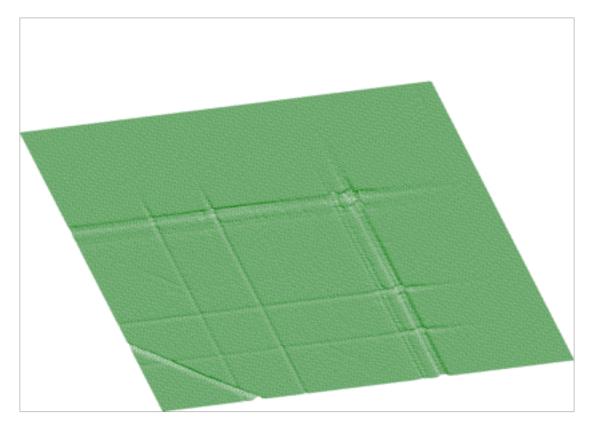


Figure 1.16: Experimental spectrum with estimated background

- BACK2_DECREASING_WINDOW
- filter_order order of clipping filter. Possible values:
 - BACK2_ORDER2
 - BACK2_ORDER4
 - BACK2_ORDER6
 - BACK2_ORDER8

Next we present the function that estimates the continuous background together with rectangular, and nonlinear ridges. To illustrate the data of such a form we present synthetic data shown in Figure 1.17. The estimated background is given in Figure 1.18. Pure Gaussian after subtracting the background from the original spectrum is shown in Figure 1.19

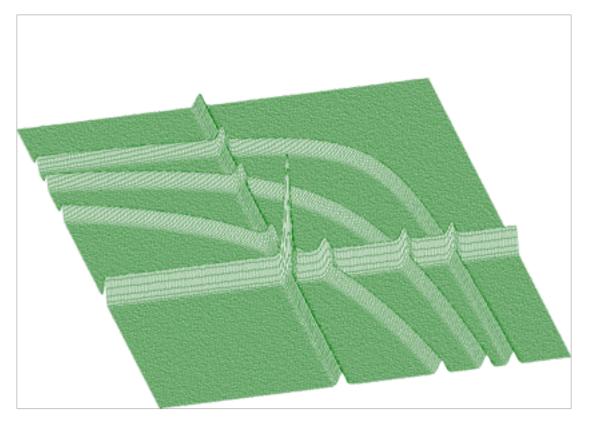


Figure 1.17: Synthetic data

The function to estimate also the nonlinear ridges has the form

char *Background2NonlinearRidges(float **spectrum,

```
int sizex,
int sizey,
int number-of-iterations-x,
int number-of-iterations-y,
int direction,
int filter_order);
```

The result is placed to the array pointed by spectrum pointer..

Function parameters:

- **spectrum** pointer to the array of source spectrum
- **sizex** x length of spectrum
- **sizey** y length of spectrum
- number_of_iterations_x maximal x width of clipping window
- **number_of_iterations_y** maximal y width of clipping window
- direction direction of change of clipping window. Possible values:

- BACK2_INCREASING_WINDOW _ BACK2_DECREASING_WINDOW

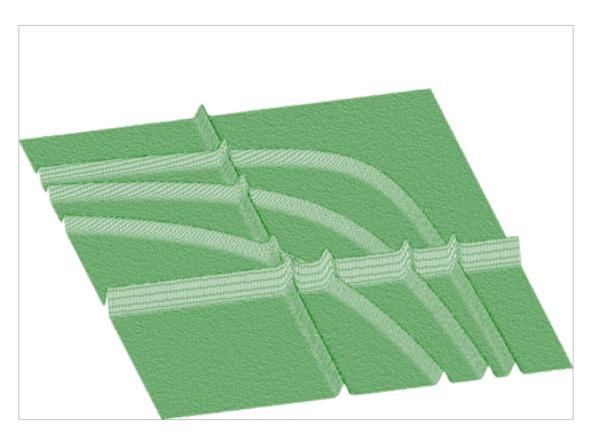


Figure 1.18: Estimated background

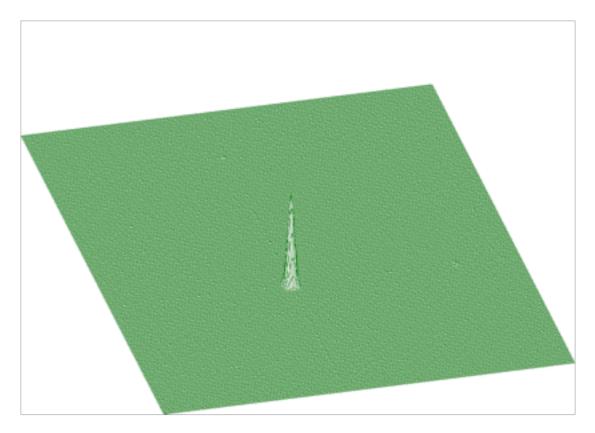


Figure 1.19: Pure Gaussian after subtracting the background from the original spectrum

- filter_order order of clipping filter. Possible values:
 - BACK2_ORDER2
 - BACK2_ORDER4
 - BACK2_ORDER6
 - BACK2_ORDER8

The information contained in the skew ridges and non-linear ridges can be interesting and one may wish to separate it from the rectangular ridges. Therefore we have implemented also two functions allowing to estimate ridges only in the direction rectangular to x- axis and y-axis. Let us have both rectangular and skew ridges from spectrum given in Figure 1.13 estimated using above described function **Background2SkewRidges**(Figure 1.20).

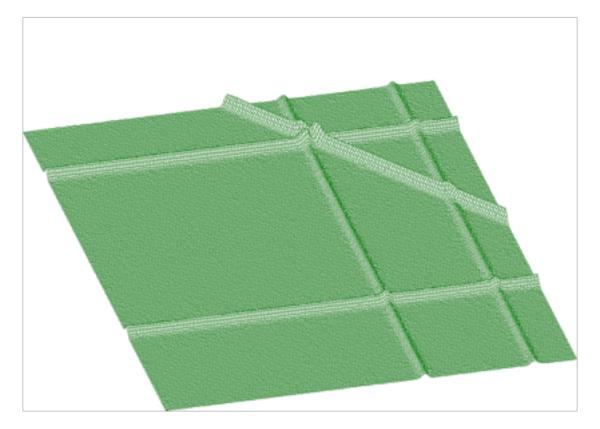


Figure 1.20: Background2SkewRidges9

Now let us estimate ridges rectangular to x-axis and y-axis (Figures 1.21, 1.22)

After subtraction these data from spectrum in Figure 1.20, we get separated skew ridge given in Figure 1.23. The functions for estimation of 1-dimensional ridges in 2-dimensional spectra have the forms

char *Background2RectangularRidgesX(float **spectrum,

```
int sizex,
int sizey,
int number-of-iterations,
int direction,
int filter_order);
```

Function parameters:

- **spectrum** pointer to the array of source spectrum
- **sizex** x length of spectrum
- **sizey** y length of spectrum
- number_of_iterations maximal x width of clipping window
- direction direction of change of clipping window. Possible values:
 - BACK2_INCREASING_WINDOW
 - BACK2_DECREASING_WINDOW

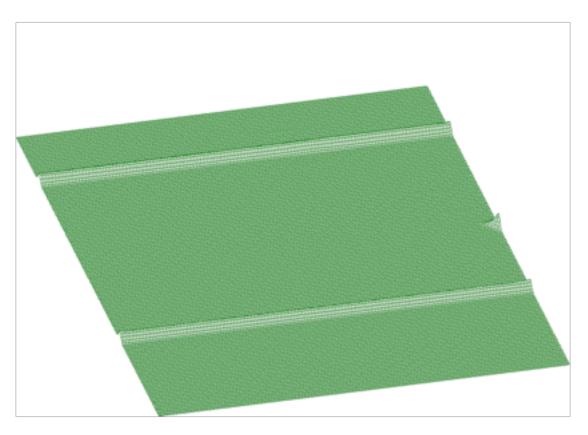


Figure 1.21: Ridges rectangular to x-axis

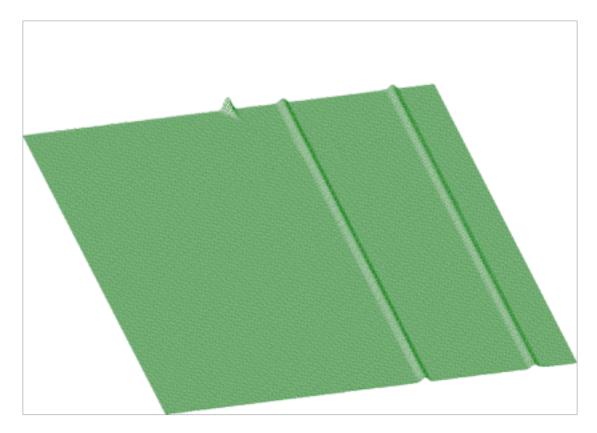


Figure 1.22: ridges rectangular to y-axis

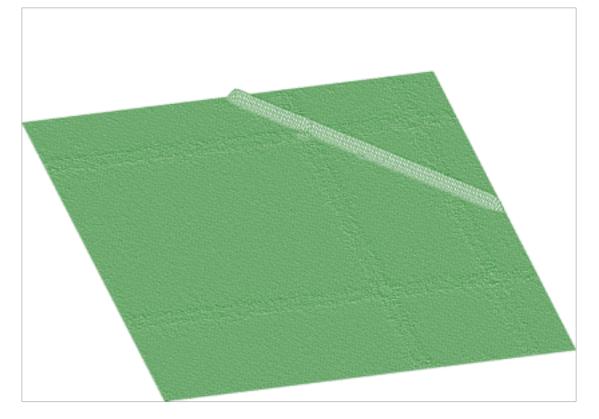


Figure 1.23: Separated skew ridge

- filter_order order of clipping filter. Possible values:
 - BACK2_ORDER2
 - BACK2_ORDER4
 - BACK2_ORDER6
 - BACK2_ORDER8

```
char *Background2RectangularRidgesY(float **spectrum,
```

int sizex, int sizey, int number_of_iterations, int direction, int filter_order);

Function parameters:

- **spectrum** pointer to the array of source spectrum
- $\mathtt{sizex} \ x \ \mathrm{length} \ \mathrm{of} \ \mathrm{spectrum}$
- **sizey** y length of spectrum
- number_of_iterations maximal width of clipping window
- direction direction of change of clipping window. Possible values:
 - BACK2_INCREASING_WINDOW
 - BACK2_DECREASING_WINDOW
- filter_order order of clipping filter. Possible values
 - BACK2_ORDER2
 - BACK2_ORDER4
 - BACK2_ORDER6
 - BACK2_ORDER8

Chapter 2

SMOOTHING

-1-DIMENSIONAL SPECTRA

The operation of the smoothing is based on the convolution of the original data with the filter of the type

(1,2,1)/4 -three points smoothing

(-3,12,17,12,-3)/35 -five points smoothing

(-2,3,6,7,6,3,-2)/21 -seven points smoothing

(-21, 14, 39, 54, 59, 54, 39, 14, -21)/231 -nine points smoothing

(-36, 9, 44, 69, 84, 89, 84, 69, 44, 9, -36)/429 -11 points smoothing

(-11,0,9,16,21,24,25,24,21,16,9,0,-11)/143 -13 points smoothing

(-78, -13, 42, 87, 122, 147, 162, 167, 162, 147, 122, 87, 42, -13, -78)/1105 -15 points smoothing. The function for one-dimensional smoothing has the form

This function calculates smoothed spectrum from source spectrum. The result is placed in the vector pointed by spectrum pointer.

Function parameters:

- spectrum pointer to the vector of source spectrum
- **size** length of spectrum
- points width of smoothing window. Allowed values
 - SMOOTH1 3POINTS
 - SMOOTH1 5POINTS
 - SMOOTH1 7POINTS
 - SMOOTH1 9POINTS
 - SMOOTH1_11POINTS
 - SMOOTH1 13POINTS
 - SMOOTH1_15POINTS

An example of 1-dimensional spectra smoothing and the influence of the filter width on the data is presented in Figure 2.1

2.1 2-DIMENSIONAL SPECTRA

The smoothing of the two dimensional data is analogous to the one dimensional case. The width of filter can be chosen independently for each dimension. The form of the 2-D smoothing function is as follows

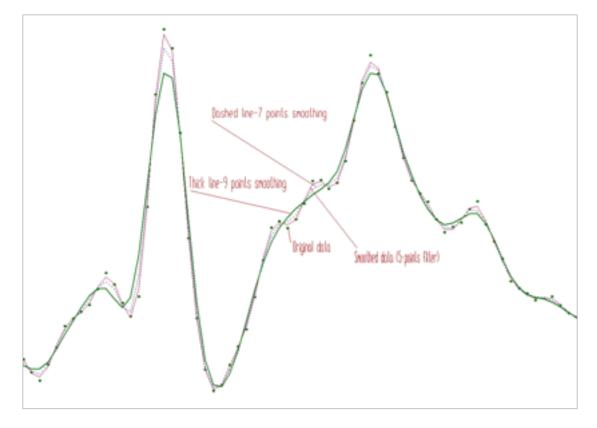


Figure 2.1: 1-dimensional spectra smoothing and the influence of the filter width on the data

int pointsy);

This function calculates smoothed spectrum from source spectrum. The result is placed in the array pointed by spectrum pointer.

Function parameters:

- **spectrum** pointer to the array of source spectrum
- **sizex** x length of spectrum
- sizey y length of spectrum
- pointsx, pointsy width of smoothing window. Allowed values:
 - SMOOTH2_3POINTS
 - SMOOTH2_5POINTS
 - SMOOTH2_7POINTS
 - SMOOTH2_9POINTS
 - SMOOTH2_11POINTS
 - SMOOTH2_13POINTS
 - SMOOTH2_15POINTS

An example of 2-D original data and data after smoothing is given in Figures 2.2, 2.3.

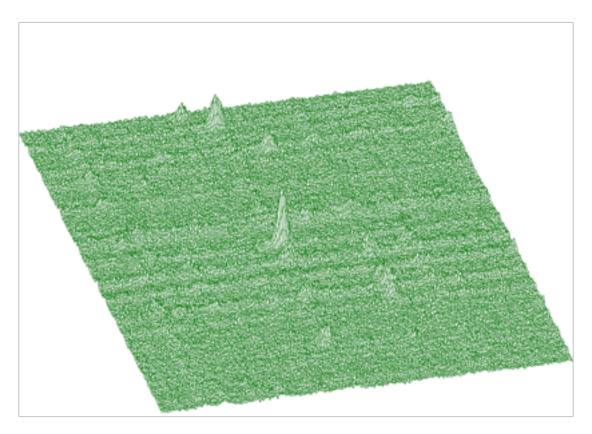


Figure 2.2: 2-D original data

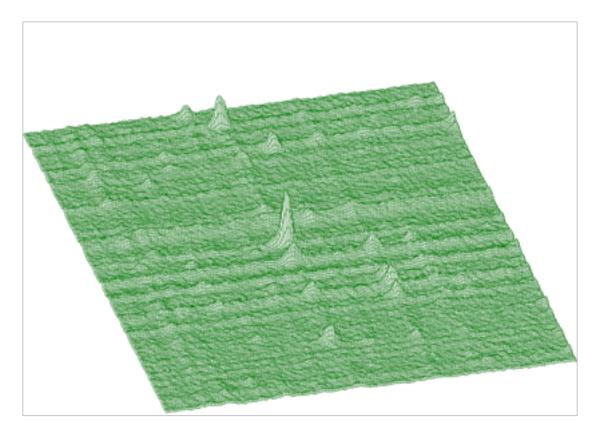


Figure 2.3: Data after smoothing

Chapter 3

PEAK SEARCHING

3.1 1-DIMENSIONAL SPECTRA

The basic function of the 1-dimensional peak searching is in detail described in [4], [5]. It allows to identify automatically the peaks in a spectrum with the presence of the continuous background and statistical fluctuations - noise. The algorithm is based on smoothed second differences that are compared to its standard deviations. Therefore it is necessary to pass a parameter of sigma to the peak searching function. The algorithm is selective to the peaks with the given sigma. The form of the basic peak searching function is

This function searches for peaks in source spectrum. The number of found peaks and their positions are written into structure pointed by one_dim_peak structure pointer.

Function parameters:

- ${\tt source}$ pointer to the vector of source spectrum
- **p** pointer to the one_dim_peak structure pointer
- **size** length of source spectrum
- sigma sigma of searched peaks

The structure one_dim_peak has the form:

```
struct one_dim_peak{
    int number_of_peaks;
    double position[MAX_NUMBER_OF_PEAKS1];
};
```

An example of simple one-dimensional spectrum with identified peaks is given in Figure 3.1.

An example of 1-dimensional experimental spectrum with many identified peaks is given in Figure 3.2.

However when we have noisy data the number of peaks can be enormous. One such an example is given in Figure 3.3. Therefore it can be useful to have possibility to set a threshold value and to consider only the peaks higher than this threshold (see Figure 3.4, only three peaks were identified, threshold=50.) The value in the center of the peak value[i] minus the average value in two symmetrically positioned channels (channels i- 3^* sigma, i+ 3^* sigma) must be greater than threshold. Otherwise the peak is ignored.

An alternative approach was proposed in [6].. The algorithm generates new invariant spectrum based on discrete Markov chains. In this spectrum the noise is suppressed, the spectrum is smoother than the original one. On the other hand it emphasizes peaks (depending on the averaging window). The example of the part of original noisy spectrum and Markov spectrum for window=3 is given in Figure 3.5 Then the peaks can found in Markov spectrum using standard above presented algorithm.

The form of the generalized peak searching function is as follows.

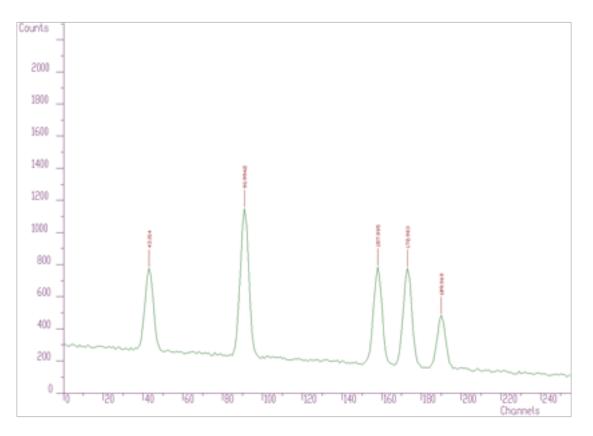


Figure 3.1: Simple one-dimensional spectrum with identified peaks

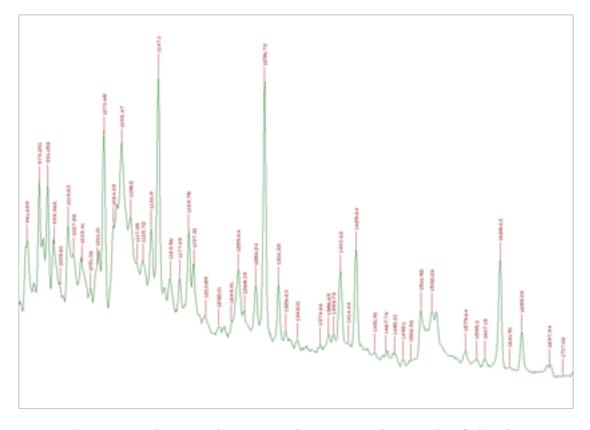


Figure 3.2: 1-dimensional experimental spectrum with many identified peaks

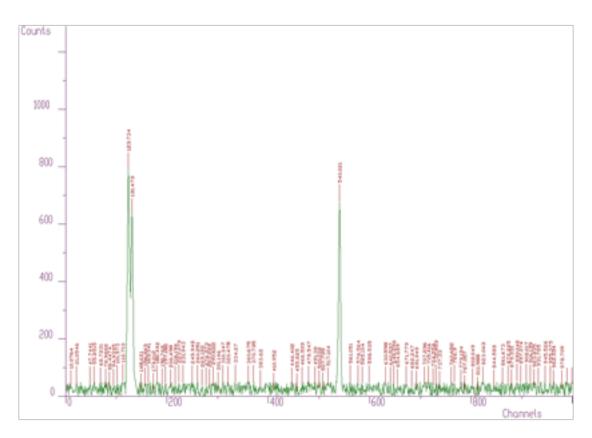


Figure 3.3: With noisy data the number of peaks can be enormous

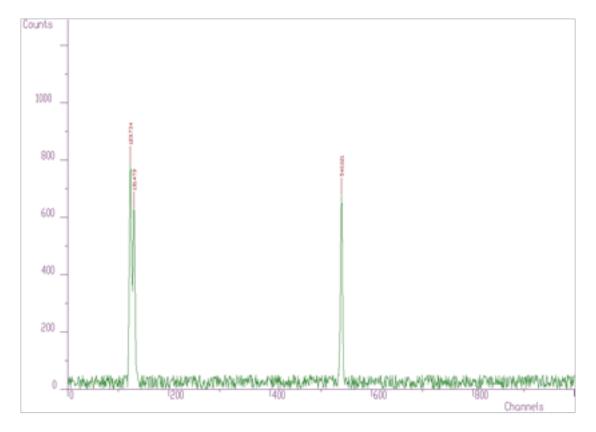


Figure 3.4: Iwth threshold=50, only three peaks were identified

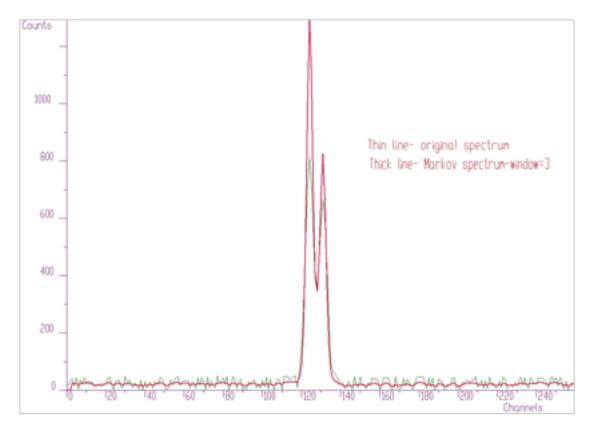


Figure 3.5: Part of original noisy spectrum and Markov spectrum for window=3

```
Int-t Search1General(float *spectrum,
```

```
int size,
float sigma,
int threshold,
bool markov,
int aver-window);
```

This function searches for peaks in source spectrum. The number of found peaks and their positions are written into structure pointed by one_dim_peak structure pointer.

Function parameters:

- **spectrum** pointer to the vector of source spectrum source spectrum is replaced by new spectrum calculated using Markov chains method.
- size length of source spectrum
- **sigma** sigma of searched peaks
- threshold threshold value for selecting of peaks
- markov logical variable, if it is true, first the source spectrum is replaced by new spectrum calculated using Markov chains method.
- aver_window averaging window used in calculation of Markov spectrum, applies only for markov variable is true

The methods of peak searching are sensitive to the sigma. Usually the sigma value is known beforehand. It also changes only slightly with the energy. We have investigated as well the robustness of the proposed algorithms to the spectrum with the peaks with sigma changing from 1 to 10 (see Figure 3.6).

We applied peak searching algorithm based on Markov approach. We changed sigma in the interval from 1 to 10. The spectra for averaging windows 3, 5, 10 are shown in Figure 3.7.

When we applied peak searching function to the Markov spectrum averaged with the window=10, we obtained correct estimate of all 10 peak positions for sigma=2,3,4,5,6,7,8. It was not the case when we made the same experiment with the original spectrum. For all sigmas some peaks were not discovered.

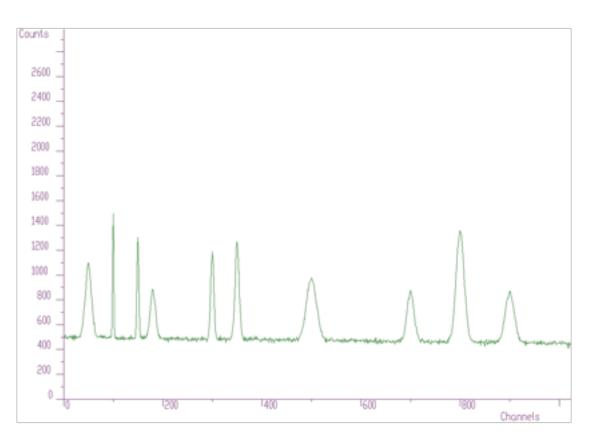


Figure 3.6: Robustness of the proposed algorithms to the spectrum with the peaks with sigma changing from 1 to 10

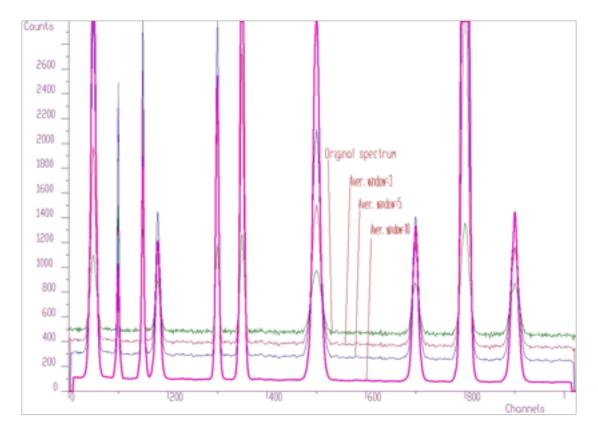


Figure 3.7: Spectra for averaging windows 3, 5, 10 $\,$

3.2 2-DIMENSIONAL SPECTRA

The basic function of the 2-dimensional peak searching is in detail described in [4].. It identifies automatically the peaks in a spectrum with the presence of the continuous background, statistical fluctuations as well as coincidences of background in one dimension and peak in the other one-ridges. The form of the basic function of 2-dimensional peak searching is

This function searches for peaks in source spectrum .The number of found peaks and their positions are written into structure pointed by two_dim_peak structure pointer.

Function parameters:

- **source** pointer to the vector of source spectrum
- sizex x length of source spectrum
- sizey y length of source spectrum
- **sigma** sigma of searched peaks

An example of the two-dimensional spectrum with the identified peaks is shown in Figure 3.8.

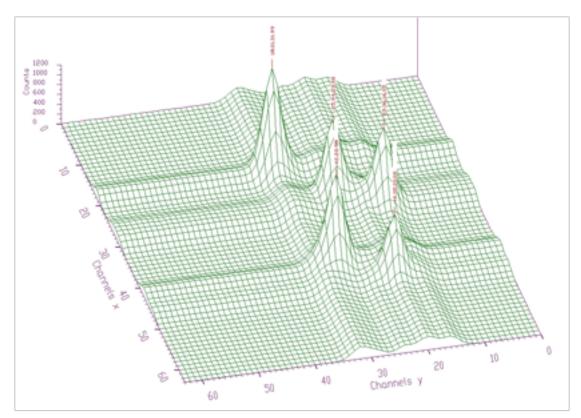


Figure 3.8: Two-dimensional spectrum with the identified peaks

We have also generalized the peak searching function analogously to one dimensional data. The generalized peak searching function for two dimensional spectra has the form

bool markov, int aver-window);

3.2. 2-DIMENSIONAL SPECTRA

This function searches for peaks in source spectrum. The number of found peaks and their positions are written into structure pointed by two_dim_peak structure pointer.

Function parameters:

- ${\tt source}$ pointer to the vector of source spectrum
- $\mathtt{sizex} \ x$ length of source spectrum
- **sizey** y length of source spectrum
- **sigma** sigma of searched peaks
- threshold threshold value for selection of peaks
- markov logical variable, if it is true, first the source spectrum is replaced by new spectrum calculated using Markov chains method.
- aver_window averaging window of searched peaks (applies only for Markov method)

An example of experimental 2-dimensional spectrum is given in Figure 3.9. The number of peaks identified by the function now is 295.

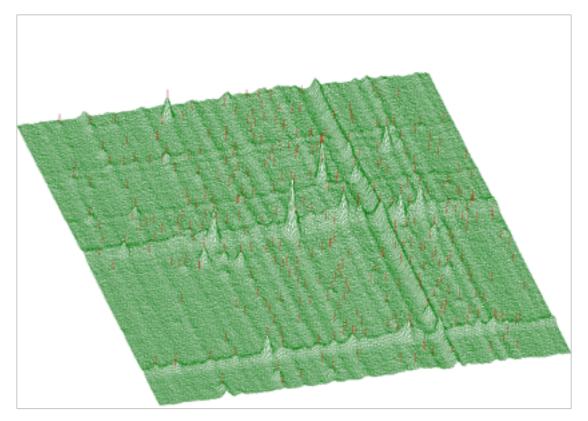


Figure 3.9: Experimental 2-dimensional spectrum

The function works even for very noisy data. In Figure 3.10 we present synthetic 2-dimensional spectrum with 5 peaks. The method should recognize what is real 2-dimensional peak and what is the crossing of two 1-dimensional ridges The Markov spectrum with averaging window=3 is given in Figure 3.11. One can observe that this spectrum is smoother than the original one. After applying the general peak searching function to the Markov spectrum with sigma=2, and threshold=600, we get correctly identified peaks.

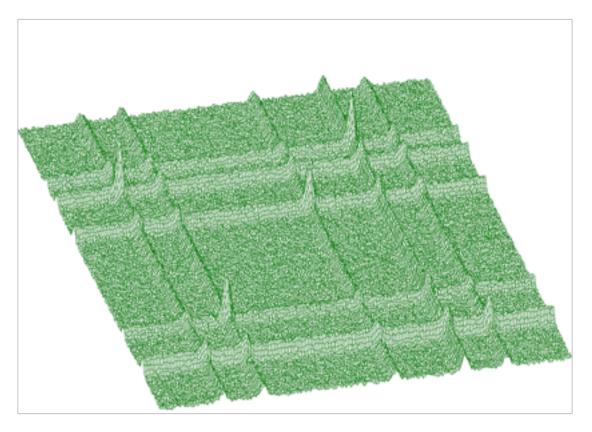


Figure 3.10: Synthetic 2-dimensional spectrum with 5 peaks

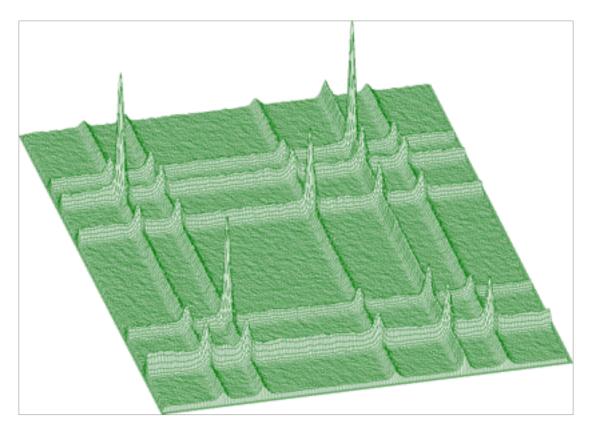


Figure 3.11: Markov spectrum with averaging window=3

Chapter 4

DECONVOLUTION - UNFOLDING

4.1 1-DIMENSIONAL SPECTRA

Mathematical formulation of the convolution system is:

$$y(i) = \sum_{k=0}^{N-1} h(i-k)x(k), i = 0, 1, 2, ..., N-1$$

where h(i) is the impulse response function, x, y are input and output vectors, respectively, N is the length of x and h vectors. In matrix form we have:

$$\begin{bmatrix} y(0) \\ y(1) \\ \vdots \\ \vdots \\ \vdots \\ y(2N-2) \\ y(2N-1) \end{bmatrix} = \begin{bmatrix} h(0) & 0 & 0 & 0 & \dots & 0 \\ h(1) & h(0) & 0 & 0 & \dots & 0 \\ h(1) & h(0) & 0 & 0 & \dots & 0 \\ \vdots & h(1) & h(0) & 0 & \dots & 0 \\ h(N-1) & \vdots & h(1) & h(0) & \dots & 0 \\ 0 & h(N-1) & \vdots & h(1) & \dots & 0 \\ 0 & 0 & h(N-1) & \vdots & \dots & h(0) \\ 0 & 0 & 0 & h(N-1) & \dots & h(1) \\ \vdots & \vdots & \vdots & \vdots & \vdots & \dots & \vdots \\ 0 & 0 & 0 & 0 & \dots & h(N-1) \end{bmatrix} \begin{bmatrix} x(0) \\ x(1) \\ x(2) \\ \vdots \\ y(N-1) \end{bmatrix}$$

Let us assume that we know the response and the output vector (spectrum) of the above given system. The deconvolution represents solution of the overdetermined system of linear equations, i.e., the calculation of the vector \mathbf{x} .

The goal of the deconvolution methods is to improve the resolution in the spectrum and to decompose multiplets. From mathematical point of view the operation of deconvolution is extremely critical as well as time consuming operation. From all the methods studied the Gold deconvolution (decomposition) proved to work as the best one. It is suitable to process positive definite data (e.g. histograms). In detail the method is described in [7], [8].

4.2 Gold deconvolution algorithm

• proved to work as the best, other methods (Fourier, VanCittert etc) oscillate

$$\begin{split} y &= Hx \\ H^T &= H^T Hx \\ y^{'} &= H^{'}x \\ x^{(k+1)}_i &= \frac{y^{'}_i}{\sum_{m=0}^{N-1} H^{'}_{im} x^{(k)}_m} x^{(k)}_i, i=0,1,...,N-1, \\ k &= 1,2,3,...,I \end{split}$$

where:

$$x^{(0)} = [1, 1, ..., 1]^T$$

The basic function has the form

This function calculates deconvolution from source spectrum according to response spectrum.

Function parameters:

- ${\tt source}$ pointer to the vector of source spectrum
- **resp** pointer to the vector of response spectrum
- ${\tt size}$ length of source and response spectra
- number_of_iterations for details see [8]

As an illustration of the method let us introduce small example. In Figure 4.1 we present original 1-dimensional spectrum. It contains multiplets that cannot be directly analyzed. The response function (one peak) is given in Figure 4.2. We assume the same response function (not changing the shape) along the entire energy scale. So the response matrix is composed of mutually shifted response functions by one channel, however of the same shape.

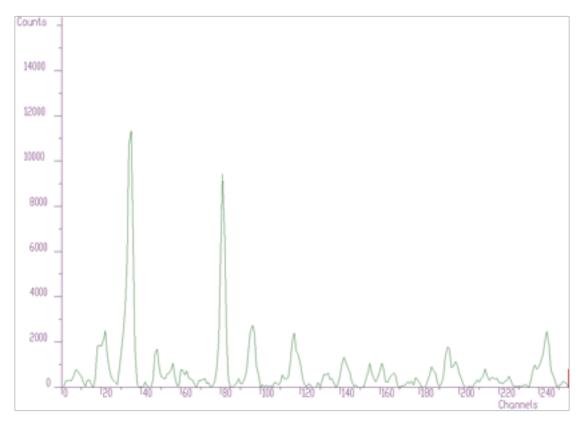


Figure 4.1: Original 1-dimensional spectrum

The result after deconvolution is given in Figure 4.3. It substantially improves the resolution in the spectrum.

We have developed a new high resolution deconvolution algorithm. We have observed that the Gold deconvolution converges to its stable state (solution). It is useless to increase the number of iterations, the result obtained does not change. To continue in decreasing the width of peaks we have found that when the solution reaches its stable state it is necessary to stop iterations, then to change the vector in a way and repeat again the Gold deconvolution . We have found that to change the particular solution we need to apply non-linear boosting function to it. The power function proved to give the best results. At the beginning the function calculates exact solution of the Toeplitz system of linear equations.

$$x^{(0)} = [x_e^2(0), x_e^2(1), ..., x_e^2(N-1),]^T$$

 $x_e = H^{'-1} y^{'}$

where :

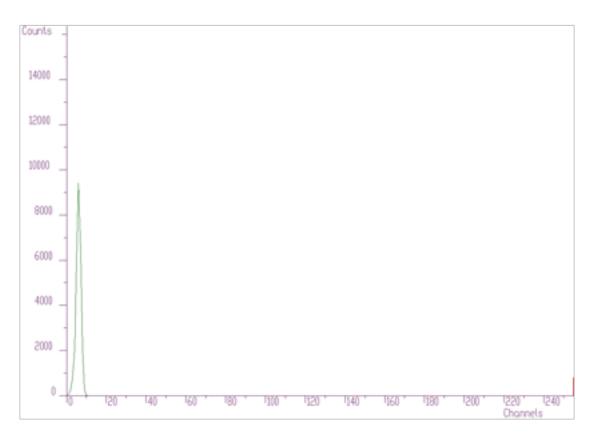


Figure 4.2: Response function (one peak)

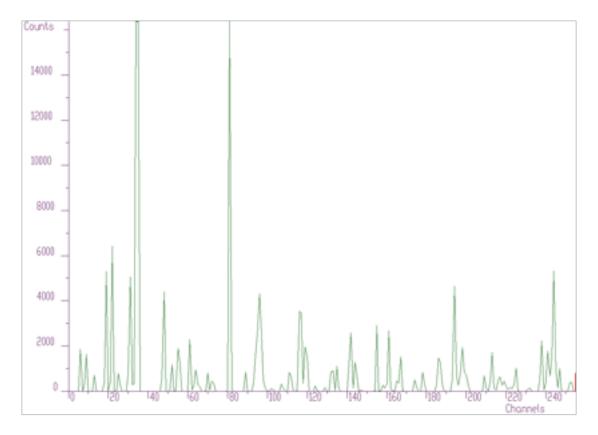


Figure 4.3: Result after deconvolution

then used as initial estimate of the solution of linear system of equations and again the Gold algorithm is employed. The whole procedure is repeated number_of_repetitions times.

The form of the high-resolution deconvolution function is

This function calculates deconvolution from source spectrum according to response spectrum

The result is placed in the vector pointed by source pointer.

Function parameters:

- source pointer to the vector of source spectrum
- **resp** pointer to the vector of response spectrum
- **size** length of source and response spectra
- number_of_iterations for details we refer to manual
- number_of_repetitions for details we refer to manual
- boost boosting factor, for details we refer to manual

The result obtained using the data from Figures 4.1, 4.2 and applying the high resolution deconvolution is given in Figure 4.4. It decomposes the peaks even more (practically to 1, 2 channels).

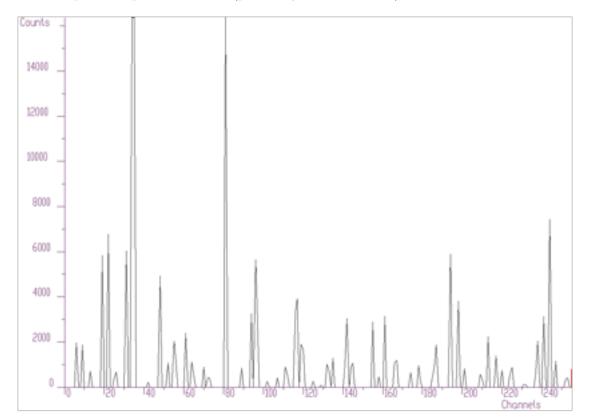


Figure 4.4: Result obtained using the data from Figures 4.1, 4.2 and applying the high resolution deconvolution

Another example of synthetic data is given in Figure 4.5. We have positioned the two peaks very close to each other (2 channels). The method of high resolution deconvolution has decomposed these peaks practically to one channel. The original data are shown as polyline, the data after deconvolution as bars. The numbers at the bars denote the heights of bars and the numbers in parenthesis the original area of peaks. The area of original peaks is concentrated into one channel.

Up to now we assumed that the shape of the response is not changing. However the method of Gold decomposition can be utilized also for the decomposition of input data (unfolding) with completely different responses. The form of the unfolding function is as follows

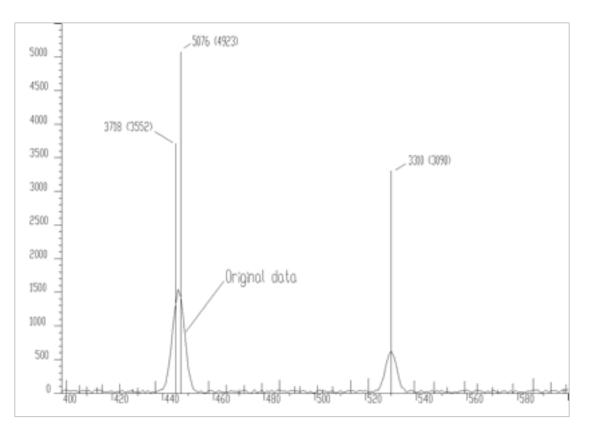


Figure 4.5: Example of synthetic data

This function unfolds source spectrum according to response matrix columns. The result is placed in the vector pointed by source pointer.

Function parameters:

- **source** pointer to the vector of source spectrum
- **resp** pointer to the matrix of response spectra
- sizex length of source spectrum and # of rows of response matrix
- **sizey** # of columns of response matrix
- number_of_iterations

Note!!! sizex must be >= sizey. After decomposition the resulting channels are written back to the first sizey channels of the source spectrum.

The example of the response matrix composed of the responses of different chemical elements is given in Figure 4.6

The original spectrum before unfolding is given in Figure 4.7. The obtained coefficients after unfolding, i.e., the contents of the responses in the original spectrum is presented in the Figure 4.8.

Another example where we have used unfolding method is the decomposition of continuum of gamma-ray spectra. Using simulation and interpolation techniques we have synthesized the response matrix (size 3400x3400 channels) of Gammasphere spectrometer (Figure 4.9). Its detail is presented in Figure 4.10. The original spectrum of Co56 before and after continuum decomposition are presented in Figures 4.11, 4.12, respectively.

4.3 2-DIMENSIONAL SPECTRA

We have extended the method of Gold deconvolution also for 2-dimensional data. Again the goal of the deconvolution methods is to improve the resolution in the spectrum and to decompose multiplets. In detail the method of optimized 2-dimensional deconvolution is described in [8].

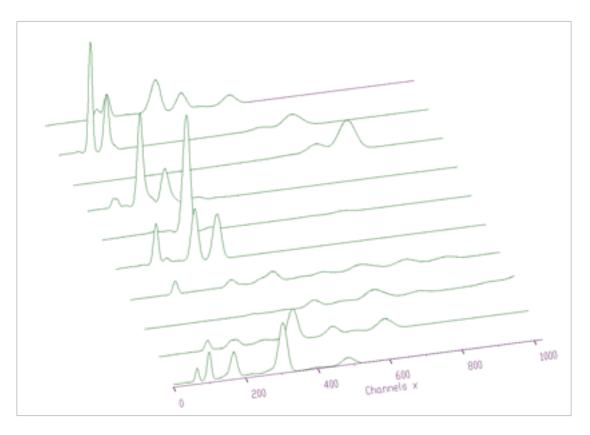


Figure 4.6: Example of the response matrix composed of the responses of different chemical elements

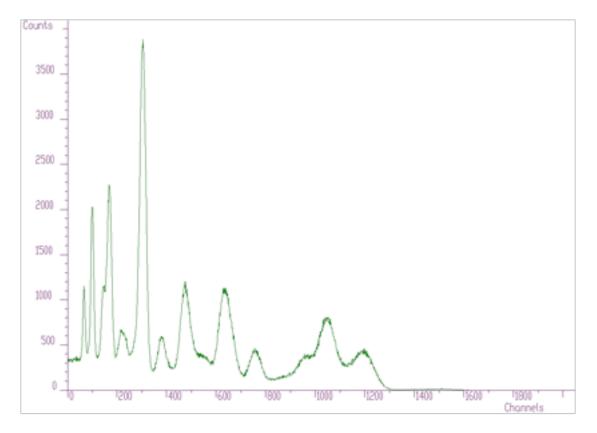


Figure 4.7: Original spectrum before unfolding

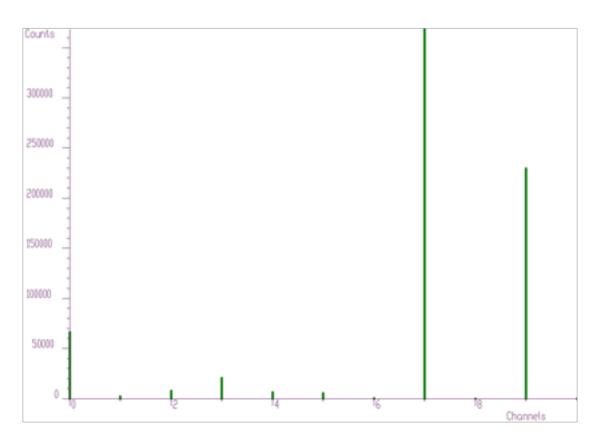


Figure 4.8: Contents of the responses in the original spectrum

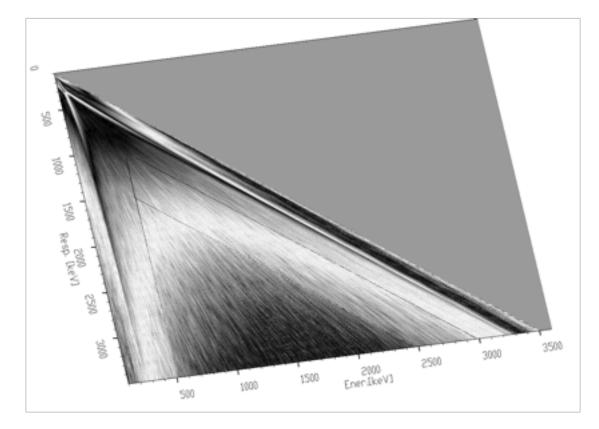


Figure 4.9: Response matrix (size 3400x3400 channels) of Gammasphere spectrometer

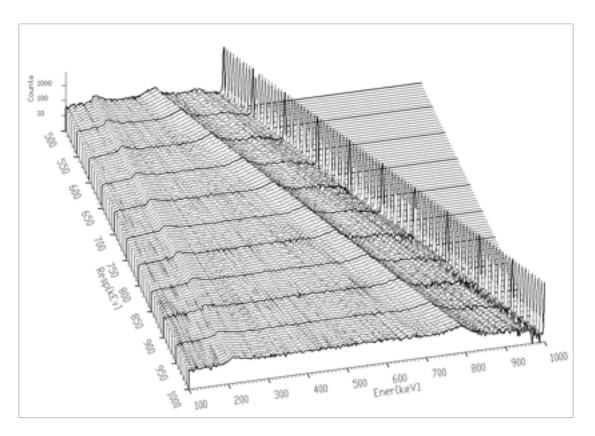


Figure 4.10: Detail of Figure 4.9

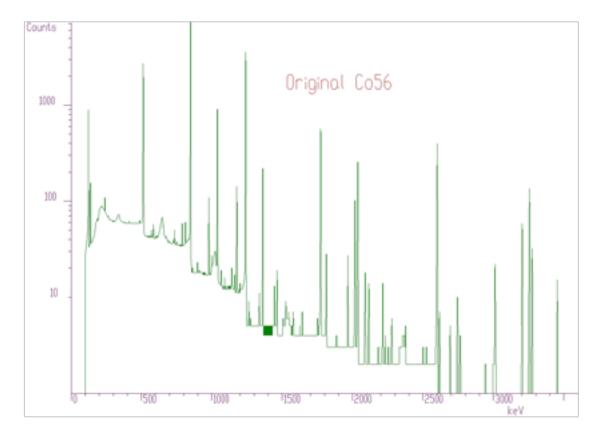


Figure 4.11: Original spectrum of Co56 before continuum decomposition

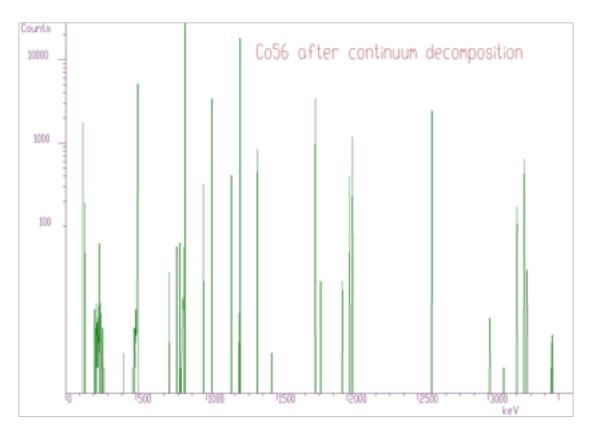


Figure 4.12: Original spectrum of Co56 after continuum decomposition

Mathematical formulation of 2-dimensional convolution system is as follows

$$y(i_1, i_2) = \sum_{k_1=0}^{N_1-1} \sum_{k_2=0}^{N_2-1} h(i_1 - k_1, i_2 - k_2) x(k_1, k_2), i_1 = 0, 1, 2, \dots, N_1 - 1, i_2 = 0, 1, 2, \dots, N_2 - 1$$

Assuming we know the output spectrum \mathbf{y} and the response spectrum \mathbf{h} , the task is to calculate the matrix \mathbf{x} . The basic function has the form

This function calculates deconvolution from source spectrum according to response spectrum. The result is placed in the matrix pointed by source pointer.

Function parameters:

- **source** pointer to the matrix of source spectrum
- **resp** pointer to the matrix of response spectrum
- sizex x length of source and response spectra
- sizey y length of source and response spectra
- number_of_iterations for details see [8]

The example of 2-dimensional spectrum before deconvolution is presented in Figure 4.13. In the process of deconvolution we have used the response matrix (one peak shifted to the beginning of the coordinate system) given in Figure 4.14. Employing the Gold deconvolution algorithm implemented in the decon2 function we get the result shown in Figure 4.15. One can notice that the peaks became narrower thus improving the resolution in the spectrum.

Analogously to 1-dimensional case we have developed high-resolution 2-dimensional deconvolution. From the beginning the exact solution of the cyclic convolution 2-dimensional system is calculated. Then we apply the repeated deconvolution with boosting in the same way like in 1- dimensional case. The form of the high-resolution 2-dimensional deconvolution function is:

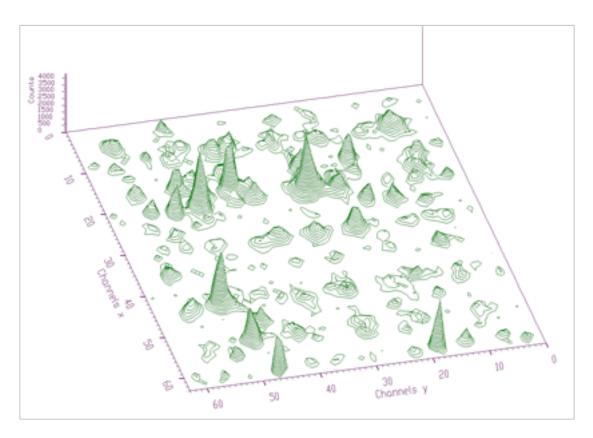


Figure 4.13: 2-dimensional spectrum before deconvolution

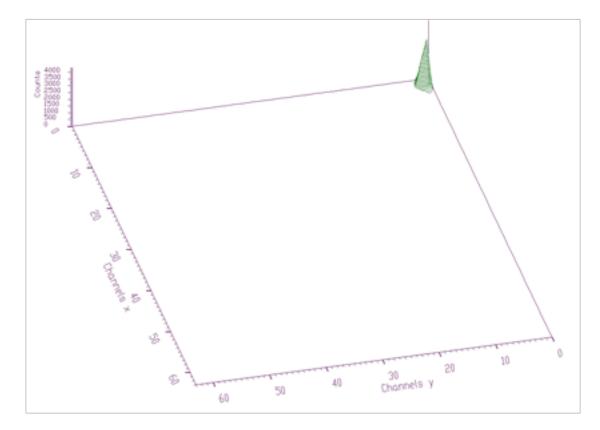


Figure 4.14: Response matrix (one peak shifted to the beginning of the coordinate system)

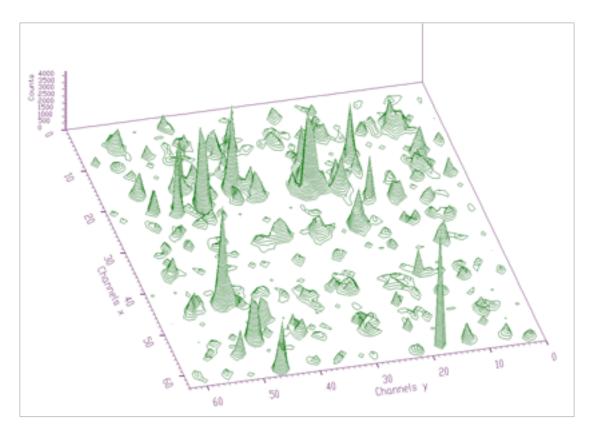


Figure 4.15: Result obtained employing the Gold deconvolution algorithm implemented in the decon2 function

```
char *Deconvolution2HighResolution(float **source,
```

```
const float **resp,
int sizex,
int sizey,
int number_of_iterations,
int number_of_repetitions,
double boost);
```

This function calculates deconvolution from source spectrum

according to response spectrum

The result is placed in the matrix pointed by source pointer.

Function parameters:

- **source** pointer to the matrix of source spectrum
- **resp** pointer to the matrix of response spectrum
- **sizex** x length of source and response spectra
- sizey y length of source and response spectra
- number_of_iterations
- number_of_repetitions
- **boost** boosting factor

When we apply this function to the data from Figure 4.13 using response matrix given in Figure 4.14 we get the result shown in Figure 4.16. It is apparent that the high-resolution deconvolution decomposes the input data even more than the original Gold deconvolution.

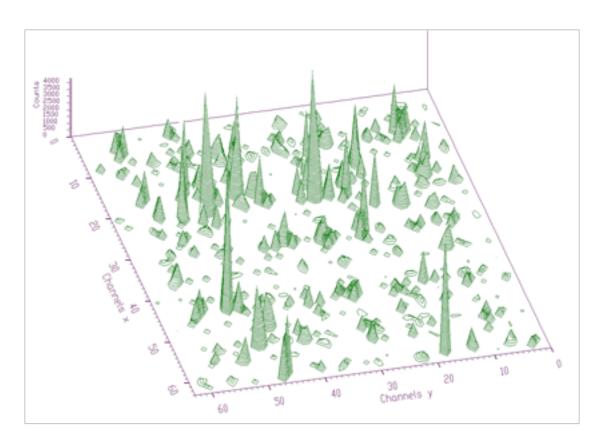


Figure 4.16: Result obtained applying Deconvolution2HighResolution to the data from Figure 4.13 using response matrix given in Figure 4.14

Chapter 5

FITTING

A lot of algorithms have been developed (Gauss-Newton, Levenber-Marquart conjugate gradients, etc.) and more or less successfully implemented into programs for analysis of complex spectra. They are based on matrix inversion that can impose appreciable convergence difficulties mainly for large number of fitted parameters. Peaks can be fitted separately, each peak (or multiplets) in a region or together all peaks in a spectrum. To fit separately each peak one needs to determine the fitted region. However it can happen that the regions of neighboring peaks are overlapping (mainly in 2-dimensional spectra). Then the results of fitting are very poor. On the other hand, when fitting together all peaks found in a spectrum, one needs to have a method that is stable (converges) and fast enough to carry out fitting in reasonable time. The gradient methods based on the inversion of large matrices are not applicable because of two reasons

- a. calculation of inverse matrix is extremely time consuming;
- b. due to accumulation of truncation and rounding-off errors the result can become worthless.

We have implemented two kinds of fitting functions. The first approach is based on the algorithm without matrix inversion [9]-awmi algorithm. It allows to fit large blocks of data and large number of parameters.

The other one is based on calculation of the system of linear equations using Stiefel-Hestens method [10]. It converges faster than awmi algorithm, however it is not suitable to fit large number of parameters.

5.1 1-DIMENSIONAL SPECTRA

• the quantity to be minimized in the fitting procedure for one dimensional spectrum is defined as :

$$\chi^{2} = \frac{1}{N - M} \sum_{i=1}^{N} \frac{[y_{i} - f(i, a)]^{2}}{y_{i}}$$

where *i* is the channel in the fitted spectrum, *N* is the number of channels in the fitting subregion, *M* is the number of free parameters, y_i is the content of the i-th channel, *a* is a vector of the parameters being fitted and f(i, a) is a fitting or peak shape function.

Instead of the weighting coefficient y_i in the denominator of the above given formula one can use also the value of f(i, a). It is suitable for data with poorstatistics [11], [12].

The third statistic to be optimized, which is implemented in the fitting functions is Maximum Likelihood Method. It is of the choice of the user to select suitable statistic..

• after differentiating χ^2 we obtain the following M simultaneous equations

$$\sum_{i=1}^{N} \frac{y_i - f(i, a^{(t)})}{y_i} \frac{\partial f(i, a^t)}{\partial a_k} = \sum_{j=1}^{M} \sum_{i=1}^{N} \frac{\partial f(i, a^{(t)})}{\partial a_j} \frac{\partial f(i, a^{(t)})}{\partial a_k} \Delta a_j^{(t)}$$

 in γ-ray spectra we have to fit together tens, hundreds of peaks simultaneously that represent sometimes thousands of parameters.

- the calculation of the inversion matrix of such a size is practically impossible.
- the awmi method is based on the assumption that off-diagonal terms in the matrix A are equal to zero.

$$\Delta a_{k}^{(t+1)} = \alpha^{(t)} \frac{\sum_{i=1}^{N} \frac{e_{i}^{(t)}}{y_{i}} \frac{\partial f(i, a^{(t)})}{\partial a_{k}}}{\sum_{i=1}^{N} \left[\frac{\partial f(i, a^{(t)})}{\partial a_{k}}\right]^{2} \frac{1}{y_{i}}}$$

where the error in the channel *i* is $e_i^{(t)} = y_i - f(i, a^{(t)})$; k = 1, 2, ..., M and $\alpha^{(t)} = 1$ if the process is convergent or $\alpha^{(t)} = 0.5\alpha^{(t-1)}$ if it is divergent. Another possibility is to optimize this coefficient.

the error of k-th parameter estimate is

$$\Delta a_k^{(e)} = \sqrt{\frac{\sum_{i=1}^N \frac{e_i^2}{y_i}}{\sum_{i=1}^N \left[\frac{\partial f(i,a^{(t)})}{\partial a_k}\right]^2 \frac{1}{y_i}}}$$

algorithm with higher powers w=1,2,3...

$$\Delta a_{k,w}^{(t+1)} = \alpha^{(t)} \frac{\sum_{i=1}^{N} \frac{e_i}{y_i} \left[\frac{\partial f(i, a^{(t)})}{\partial a_k}\right]^{2w-1}}{\sum_{i=1}^{N} \left[\frac{\partial f(i, a^{(t)})}{\partial a_k}\right]^{2w} \frac{1}{y_i}}$$

we have implemented the nonsymmetrical semiempirical peak shape function.

it contains the symmetrical Gaussian as well as nonsymmetrical terms.

$$f(i,a) = \sum_{i=1}^{M} A(j) \left\{ exp\left[\frac{-(i-p(j))^2}{2\sigma^2}\right] + \frac{1}{2}T.exp\left[\frac{(i-p(j))}{B\sigma}\right].erfc\left[\frac{(i-p(j))}{\sigma} + \frac{1}{2B}\right] + \frac{1}{2}S.erfc\left[\frac{(i-p(j))}{\sigma}\right] \right\}$$

where T, S are relative amplitudes and B is a slope.

Detailed description of the algorithm is given in [13].

The fitting function implementing the algorithm without matrix inversion has the form

This function fits the source spectrum. The calling program should fill in input parameters of the one_dim_fit structure The fitted parameters are written into structure pointed by one_dim_fit structure pointer and fitted data are written into source spectrum.

Function parameters:

- $\operatorname{\textbf{source}}$ pointer to the vector of source spectrum
- **p** pointer to the one_dim_fit structure pointer
- **size** length of source spectrum

The one_dim_fit structure has the form:

```
class TSpectrumOneDimFit{
```

```
public:
```

```
int number_of_peaks; // input parameter, should be >0
int number_of_iterations; // input parameter, should be >0
int xmin; // first fitted channel
int xmax; // last fitted channel
```

<pre>double alpha;</pre>	_	efficient, input parameter, it should be	
	// positive numbe		
double chi;	// here the function returns resulting chi-square		
<pre>int statistic_type;</pre>	<pre>// type of statis</pre>	tics, possible values	
	// FIT1_OPTIM_CH1	COUNTS (chi square statistics with	
	// counts as weig	hting coefficients),	
	// FIT1_OPTIM_CH1	[_FUNC_VALUES (chi square statistics	
	<pre>// with function</pre>	values as weighting coefficients)	
	// FIT1_OPTIM_MAX	LIKELIHOOD	
<pre>int alpha_optim;</pre>	// optimization c	f convergence coefficients, possible values	
	// FIT1_ALPHA_HAL	.VING,	
	// FIT1_ALPHA_OP1	TIMAL	
<pre>int power;</pre>	// possible value	es FIT1_FIT_POWER2,4,6,8,10,12	
<pre>int fit_taylor;</pre>	// order of Taylc	r expansion, possible values	
	// FIT1_TAYLOR_OR	RDER_FIRST, FIT1_TAYLOR_ORDER_SECOND	
double position_init[MA	X_NUMBER_OF_PEAKS1];	// initial values of	
	·	// peaks positions, input parameters	
double position_calc[MA	X NUMBER OF PEAKS1];		
	·	<pre>// of fitted positions, output parameters</pre>	
<pre>double position_err[MAX</pre>	_NUMBER_OF_PEAKS1];	// position errors	
<pre>bool fix_position[MAX_NUMBER_OF_PEAKS1];</pre>		// logical vector which allows to fix	
		// appropriate positions (not fit). However they	
		// are present in the estimated functional	
<pre>double amp_init[MAX_NUM</pre>	<pre>BER_OF_PEAKS1];</pre>	// initial values of peaks	
		// amplitudes, input parameters	
<pre>double amp_calc[MAX_NUMBER_OF_PEAKS1];</pre>		// calculated values of	
·		// fitted amplitudes, output parameters	
<pre>double amp_err[MAX_NUMBER_OF_PEAKS1];</pre>		// amplitude errors	

double amp_err[MAX_NUMBER_OF_PEAKS1]; bool fix_amp[MAX_NUMBER_OF_PEAKS1];

double area[MAX_NUMBER_OF_PEAKS1];
double area_err[MAX_NUMBER_OF_PEAKS1];

double sigma calc;

double sigma_init // sigma parameter, see peak shape function

// logical vector, which allows to fix

// calculated areas of peaks

// errors of peak areas

// are present in the estimated functional

// appropriate amplitudes (not fit). However they

double sigma_err; bool fix_sigma; // t parameter, , see peak shape function double t_init double t_calc; double t_err; bool fix_t; // b parameter, , see peak shape function double b_init double b_calc; double b_err; bool fix_b; // s parameter, , see peak shape function double s_init; double s_calc; double s_err; bool fix_s; double a0_init; // backgroud is estimated as a0+a1*x+a2*x*x double a0_calc; double a0_err; bool fix_a0; double a1_init; double a1_calc; double a1_err; bool fix_a1; double a2 init; double a2_calc; double a2_err; bool fix_a2;

As an example we present simple 1-dimensional synthetic spectrum with 5 peaks. The fit obtained using above given awmi fitting function is given in Figure 5.1. The chi-square achieved in this fit was 0.76873. The input value of the fit (positions of peaks and their amplitudes) were estimated using peak searching function.

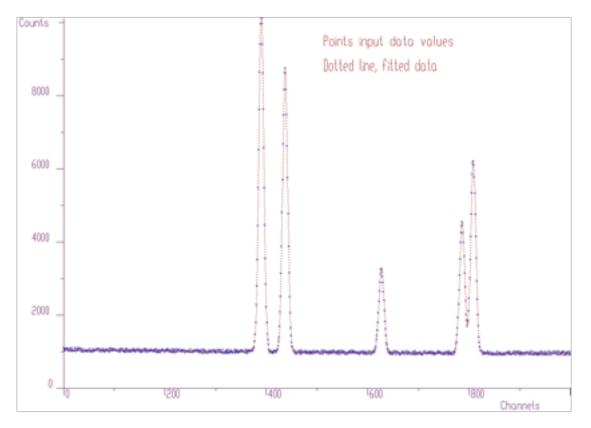


Figure 5.1: Fit obtained using above given awmi fitting function

Let us go to more complicated fit with lot of overlapping peaks Figure 5.2. The initial positions of peaks were determined from original data, using peak searching function. The fit is not very good, as there are some peaks missing.

However to analyze the spectrum we can proceed in completely different way employing the sophisticated functions of background elimination and deconvolution. First let us remove background from the original raw data. We get spectrum given in Figure 5.3.

Then we can apply the Gold deconvolution function to these data. We obtain result presented in Figure 5.4.

Using peaks searching method, looking just for local maxima, (sigma=0) with appropriate threshold (50), we can estimate initial positions of peaks for fitting function. After the fit of the original experimental spectrum (with background) we obtain the result shown in Figure 5.5. Now the fitted function corresponds much better to experimental values

We have implemented also the fitting function with matrix inversion based on Stiefel-Hestens method of the solution of the system of linear equations. The form of the function is as follows

This function fits the source spectrum. The calling program should fill in input parameters of the one_dim_fit structure The fitted parameters are written into structure pointed by one_dim_fit structure pointer and fitted data are written into source spectrum.

Function parameters:

- **source** pointer to the vector of source spectrum
- **p** pointer to the one_dim_fit structure pointer
- size length of source spectrum

};

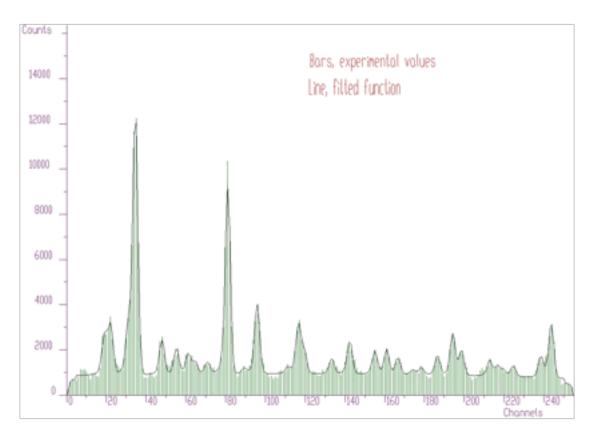


Figure 5.2: More complicated fit with lot of overlapping peaks

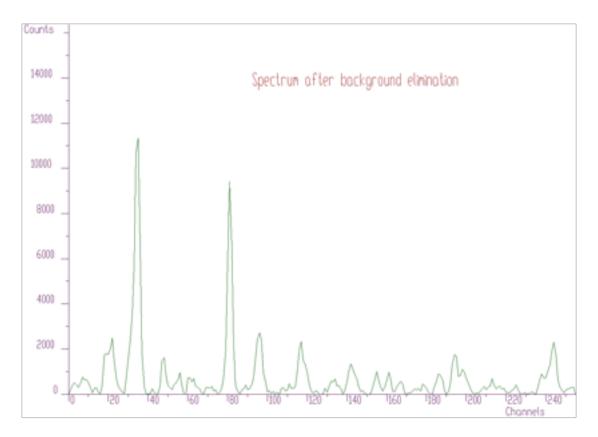


Figure 5.3: Removed background from the original raw data

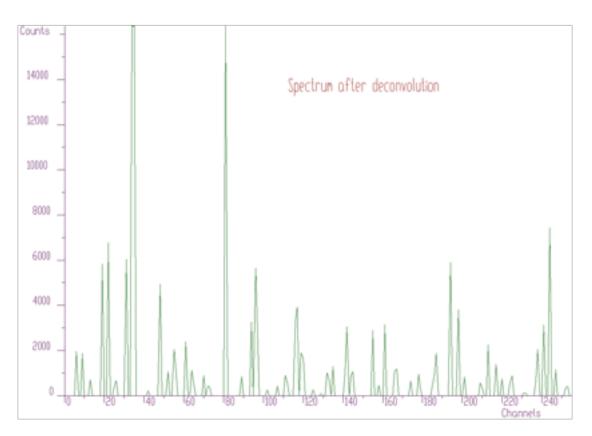


Figure 5.4: Gold deconvolution function applied to the data

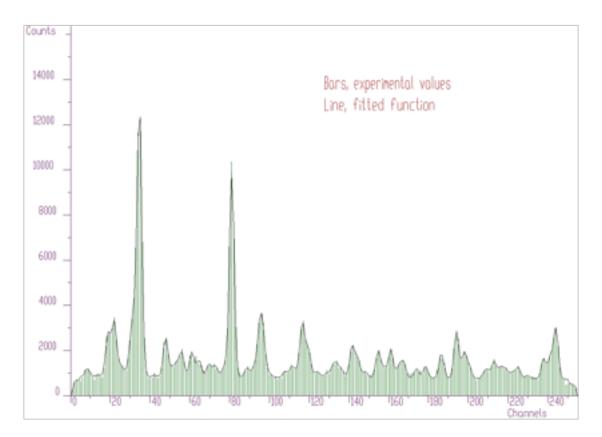


Figure 5.5: Fit of the original experimental spectrum (with background)

The structure one_dim_fit is the same as in awmi function. The parameters power, fit_taylor are not applicable for this function

The results for small number of fitted parameters are the same as with awmi function. However it converges faster. The example for data given in Figure 5.1 is given in the following table:

# of iterationsi	Chi awmi	Chi-Stiefel	
1	924	89.042	
5	773.15	0.96242	
10	38.13	0.77041	
50	0.90293	0.76873	
100	0.76886	0.76873	
500	0.76873	0.76873	

5.2 2-DIMENSIONAL SPECTRA

it is straightforward that for two dimensional spectra one can write

$$\Delta a_k^{(t+1)} = \alpha^{(t)} \frac{\sum_{i_1=1}^{N_1} \sum_{i_2=1}^{N_2} \frac{e_{i_1,i_2}^{(t)}}{y_{i_1,i_2}} \frac{\partial f(i_1,i_2,a^{(t)})}{\partial a_k}}{\sum_{i_1=1}^{N_1} \sum_{i_2=1}^{N_2} \left[\frac{\partial f(i_1,i_2,a^{(t)})}{\partial a_k}\right]^2 \frac{1}{y_{i_1,i_2}}}$$

analogously for two dimensional peaks we have chosen the peak shape function of the following form

$$f(i_1, i_2, a) = \sum_{j=1}^M \left\{ \begin{array}{l} A_{xy}(j)exp \left\{ -\frac{1}{2(1-\rho^2)} \left[\frac{(i_1 - p_x(j))^2}{\sigma_x^2} - \frac{2\rho(i_1 - p_x(j))(i_2 - p_y(j))}{\sigma_x \sigma_y} + \frac{(i_2 - p_y(j))^2}{\sigma_y^2} \right] \right\} \\ + A_x(j)exp \left[-\frac{(i_1 - p_{x_1}(j))^2}{2\sigma_x^2} \right] + A_y(j)exp \left[-\frac{(i_2 - p_{y_1}(j))^2}{2\sigma_y^2} \right] \end{array} \right\} \\ + b_0 + b_1i_1 + b_2i_2 + b_0 + b_0 + b_1i_1 + b_2i_2 + b_0 + b_$$

The meaning of the parameters is analogous to 1-dimensional case. Again all the details can be found in [13] The fitting function implementing the algorithm without matrix inversion for 2-dimensional data has the form

```
char* Fit2Awmi(float **source,
        TSpectrumTwoDimFit* p,
        int sizex,
        int sizey);
```

This function fits the source spectrum. The calling program should fill in input parameters of the two_dim_fit structure The fitted parameters are written into structure pointed by two_dim_fit structure pointer and fitted data are written back into source spectrum.

Function parameters:

- **source** pointer to the matrix of source spectrum
- **p** pointer to the two_dim_fit structure pointer, see manual
- **sizex** length x of source spectrum
- sizey length y of source spectrum

The two_dim_fit structure has the form

```
class TSpectrumTwoDimFit{
```

public:

int number_of_peaks; // input parameter, shoul be>0

```
int number_of_iterations; // input parameter, should be >0
int xmin;
                          // first fitted channel in x direction
int xmax;
                          // last fitted channel in x direction
int ymin;
                         // first fitted channel in y direction
                         // last fitted channel in y direction
int ymax;
double alpha;
                         // convergence coefficient, input parameter, it should be positive
                          // number and <=1</pre>
                          // here the function returns resulting chi square
double chi;
int statistic_type;
                          // type of statistics, possible values
                          // FIT2_OPTIM_CHI_COUNTS (chi square statistics with
                          // counts as weighting coefficients),
                          // FIT2_OPTIM_CHI_FUNC_VALUES (chi square statistics
                          // with function values as weighting
                          // coefficients),FIT2_OPTIM_MAX_LIKELIHOOD
int alpha_optim;
                          // optimization of convergence coefficients, possible values
                          // FIT2_ALPHA_HALVING, FIT2_ALPHA_OPTIMAL
                          // possible values FIT21_FIT_POWER2,4,6,8,10,12
int power;
                          // order of Taylor expansion, possible values
int fit_taylor;
                          // FIT2_TAYLOR_ORDER_FIRST,
                          // FIT2_TAYLOR_ORDER_SECOND
double position_init_x[MAX_NUMBER_OF_PEAKS2]; // initial values of x
                                               // positions of 2D peaks, input parameters
                                               // calculated values
double position_calc_x[MAX_NUMBER_OF_PEAKS2];
                                               // of fitted x positions of 2D peaks, output parameters
double position_err_x[MAX_NUMBER_OF_PEAKS2];
                                               // x position errors of 2D peaks
bool fix_position_x[MAX_NUMBER_OF_PEAKS2];
                                               // logical vector which allows to fix appropriate
                                               // x positions of 2D peaks (not fit).
                                               // However they are present in the estimated functional
double position_init_y[MAX_NUMBER_OF_PEAKS2];
                                               // initial values of y
                                               // positions of 2D peaks, input parameters
double position_calc_y[MAX_NUMBER_OF_PEAKS2];
                                               // calculated values
                                               // of fitted y positions of 2D peaks, output parameters
double position_err_y[MAX_NUMBER_OF_PEAKS2];
                                               // y position errors of 2D peaks
bool fix_position_y[MAX_NUMBER_OF_PEAKS2];
                                               // logical vector which allows to fix appropriate
                                               // y positions of 2D peaks (not fit).
                                               // However they are present in the estimated functional
double position_init_x1[MAX_NUMBER_OF_PEAKS2]; // initial values of x
                                               // positions of 1D ridges, input parameters
double position_calc_x1[MAX_NUMBER_OF_PEAKS2]; // calculated values of
                                               // fitted x positions of 1D ridges, output parameters
                                               // x position errors of 1D ridges
double position_err_x1[MAX_NUMBER_OF_PEAKS2];
bool fix_position_x1[MAX_NUMBER_OF_PEAKS2];
                                               // logical vector which allows to fix appropriate
                                               // x positions of 1D ridges (not fit).
                                               // However they are present in the estimated functional
double position_init_y1[MAX_NUMBER_OF_PEAKS2]; // initial values of y
                                               // positions of 1D ridges, input parameters
double position_calc_y1[MAX_NUMBER_OF_PEAKS2]; // calculated values
                                               // of fitted y positions of 1D ridges, output parameters
double position_err_y1[MAX_NUMBER_OF_PEAKS2];
                                               // y position errors of 1D ridges
bool fix_position_y1[MAX_NUMBER_OF_PEAKS2];
                                               // logical vector which allows to fix
                                               // appropriate y positions of 1D ridges (not fit).
                                               // However they are present in the estimated functional
                                               // initial values of 2D peaks
double amp_init[MAX_NUMBER_OF_PEAKS2];
                                               // amplitudes, input parameters
                                               // calculated values of
double amp_calc[MAX_NUMBER_OF_PEAKS2];
                                               // fitted amplitudes of 2D peaks, output parameters
double amp_err[MAX_NUMBER_OF_PEAKS2];
                                               // amplitude errors of 2D peaks
bool fix_amp[MAX_NUMBER_OF_PEAKS2];
                                               // logical vector which allows
                                               // to fix appropriate amplitudes of 2D peaks (not fit).
                                               // However they are present in the estimated functional
                                               // initial values of 1D
double amp_init_x1[MAX_NUMBER_OF_PEAKS2];
                                               // ridges amplitudes, input parameters
                                               // calculated values of
double amp_calc_x1[MAX_NUMBER_OF_PEAKS2];
```

```
double amp err x1[MAX NUMBER OF PEAKS2];
bool fix_amp_x1[MAX_NUMBER_OF_PEAKS2];
double amp_init_y1[MAX_NUMBER_OF_PEAKS2];
double amp_calc_y1[MAX_NUMBER_OF_PEAKS2];
double amp_err_y1[MAX_NUMBER_OF_PEAKS2];
bool fix_amp_y1[MAX_NUMBER_OF_PEAKS2];
double volume[MAX_NUMBER_OF_PEAKS1];
double volume_err[MAX_NUMBER_OF_PEAKS1];
double sigma_init_x; // sigma x parameter
double sigma_calc_x;
double sigma_err_x;
bool fix_sigma_x;
double sigma_init_y; // sigma y parameter
double sigma_calc_y;
double sigma_err_y;
bool fix_sigma_y;
double ro_init;
                     // correlation coefficient
double ro_calc;
double ro_err;
bool fix_ro;
double txy_init;
                     // t parameter for 2D peaks
double txy_calc;
double txy_err;
bool fix_txy;
double sxy_init;
                     // s parameter for 2D peaks
double sxy_calc;
double sxy_err;
bool fix_sxy;
double tx_init;
                     // t parameter for 1D ridges (x direction)
double tx calc;
double tx_err;
bool fix_tx;
double ty_init;
                     // t parameter for 1D ridges (y direction)
double ty_calc;
double ty_err;
bool fix_ty;
double sx_init;
                     // s parameter for 1D ridges (x direction)
double sx_calc;
double sx_err;
bool fix_sx;
                     // s parameter for 1D ridges (y direction)
double sy_init;
double sy_calc;
double sy_err;
bool fix_sy;
                     // b parameter for 1D ridges (x direction)
double bx_init;
double bx_calc;
double bx_err;
bool fix_bx;
                     // b parameter for 1D ridges (y direction)
double by_init;
double by_calc;
double by_err;
bool fix_by;
                     // backgroud is estimated as a0+ax*x+ay*y
double a0 init;
double a0_calc;
double a0_err;
bool fix_a0;
```

- // fitted amplitudes of 1D ridges, output parameters
- // amplitude errors of 1D ridges
- // logical vector which alloes to fix
- // appropriate amplitudes of 1D ridges (not fit).
- // However they are present in the estimated functional
- // initial values of 1D
- // ridges amplitudes, input parameters
- // calculated values of
- // fitted amplitudes of 1D ridges, output parameters
- // amplitude errors of 1D ridges
- // logical vector which allows to fix
- // appropriate amplitudes of 1D ridges (not fit).
- // However they are present in the estimated functional
- // calculated volumes of peaks
- // errors of peak volumes

CHAPTER 5. FITTING

```
double ax_init;
double ax_calc;
double ax_err;
bool fix_ax;
double ay_init;
double ay_calc;
double ay_err;
bool fix_ay;
};
```

The example of the original spectrum and the fitted spectrum is given in Figures. 5.6, 5.7, respectively. We have fitted 5 peaks. Each peak was represented by 7 parameters, which together with sigmax, sigmay and b0 resulted in 38 parameters. The chi-square after 1000 iterations was 0.6571.

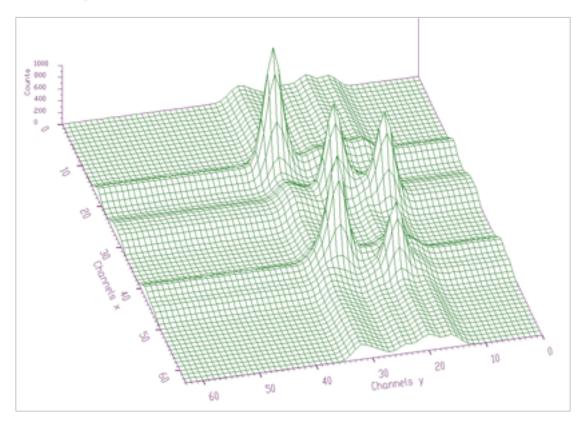


Figure 5.6: 2-dimensional Cosine transform

The awmi algorithm can be applied also to large blocks of data and large number of peaks. In the next example we present spectrum with identified 295 peaks. Each peak is represented by 7 parameters, which together with sigmax, y and b0 resulted in 2068 fitted parameters. The original spectrum and fitted function are given in Figures. 5.8, 5.9, respectively. The achieved chi-square was 0.76732.

We have implemented the fitting function with matrix inversion based on Stiefel-Hestens method of the solution of the system of linear equations also for 2-dimensional data. The form of the function is as follows

```
char* Fit2Stiefel(float **source,
        TSpectrumTwoDimFit* p,
        int sizex,
        int sizey);
```

This function fits the source spectrum. The calling program should fill in input parameters of the two_dim_fit structure The fitted parameters are written into structure pointed by two_dim_fit structure pointer and fitted data are written back into source spectrum.

- **source** pointer to the matrix of source spectrum
- p pointer to the two_dim_fit structure pointer, see manual

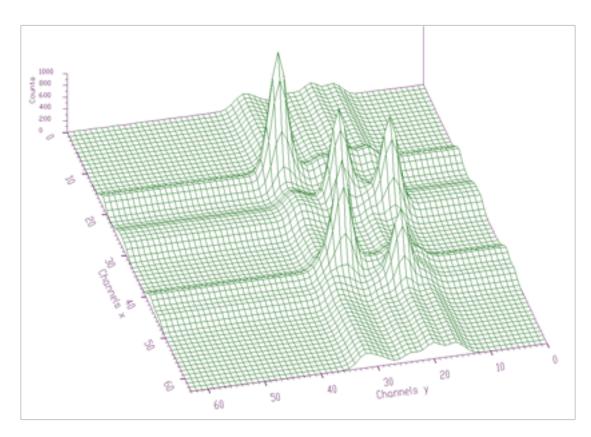


Figure 5.7: Fitted spectrum

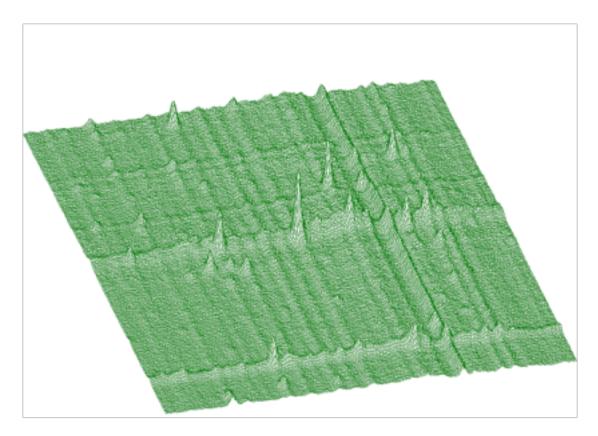


Figure 5.8: Original spectrum

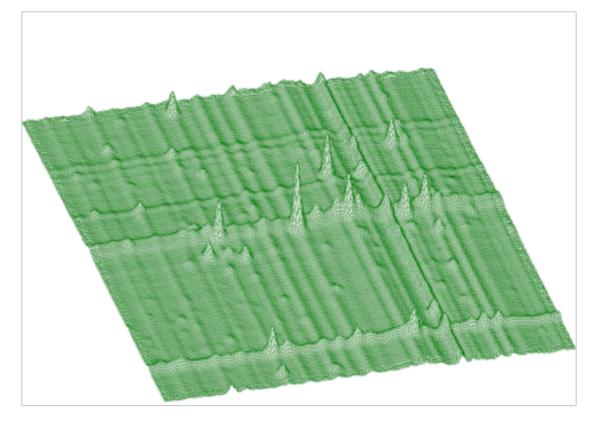


Figure 5.9: Fitted function

- \mathtt{sizex} length x of source spectrum
- **sizey** length y of source spectrum

The structure two_dim_fit is the same as in awmi function. The parameters power, fit_taylor are not applicable for this function

The results for small number of fitted parameters are the same as with awmi function. However it converges faster. The example for data given in Figure 5.6 (38 parameters) is presented in the following table:

# of iterations	Chi awmi	Chi-Stiefel	
1	24.989	10.415	
5	20.546	1.0553	
10	6.256	0.84383	
50	1.0985	0.64297	
100	0.657	1 0.64297	
500	0.651	94 0.64297	

Again Stiefel-Hestens method converges faster. However its calculation is for this number of parameters approximately 3 times longer. For larger number of parameters the time needed to calculate the inversion grows with the cube of the number of fitted parameters. For example the fit of large number of parameters (2068) for data in Figure 5.8 using awmi algorithm lasted about 12 hours (using 450 MHz PC). The calculation using matrix inversion method is not realizable in reasonable time.

Chapter 6

TRANSFORMS

6.1 1-DIMENSIONAL SPECTRA

Orthogonal transforms can be successfully used for the processing of nuclear spectra . They can be used to remove high frequency noise, to increase signal-to-background ratio as well as to enhance low intensity components [14]. We have implemented also the function for the calculation of the commonly used orthogonal transforms

- Haar
- Walsh
- Cos
- Sin
- Fourier
- Hartley

Between these transform one can define so called generalized mixed transforms that are also implemented in the transform function

- Fourier-Haar
- Fourier-Walsh
- Walsh-Haar
- Cos-Walsh
- Cos-Haar
- Sin-Walsh
- Sin-Haar

The suitability of the application of appropriate transform depends on the character of the data, i.e., on the shape of dominant components contained in the data. The form of the transform function is as follows:

```
char *Transform1(const float *source,
      float *dest,
      int size,
      int type,
      int direction,
      int degree);
```

This function transforms the source spectrum. The calling program should fill in input parameters. Transformed data are written into dest spectrum.

- source pointer to the vector of source spectrum, its length should be equal to size parameter except for inverse FOURIER, FOUR-WALSH, FOUR-HAAR transform. These need 2*size length to supply real and imaginary coefficients.
- dest pointer to the vector of dest data, its length should be equal to size parameter except for direct FOURIER, FOUR-WALSh, FOUR-HAAR. These need 2*size length to store real and imaginary coefficients

- ${\tt size}$ basic length of source and dest spectra
- type type of transform
 - TRANSFORM1_HAAR
 - TRANSFORM1_WALSH
 - TRANSFORM1_COS
 - TRANSFORM1_SIN
 - TRANSFORM1_FOURIER
 - TRANSFORM1_HARTLEY
 - TRANSFORM1_FOURIER_WALSH
 - TRANSFORM1_FOURIER_HAAR
 - TRANSFORM1_WALSH_HAAR
 - TRANSFORM1_COS_WALSH
 - TRANSFORM1_COS_HAAR
 - TRANSFORM1_SIN_WALSH
 - TRANSFORM1_SIN_HAAR
- direction transform direction (forward, inverse)
 - TRANSFORM1_FORWARD
 - TRANSFORM1_INVERSE
- **degree** applies only for mixed transforms Let us illustrate the applications of the transform using an example. In Figure 6.1 we have spectrum with many peaks, complicated background and high level of noise.

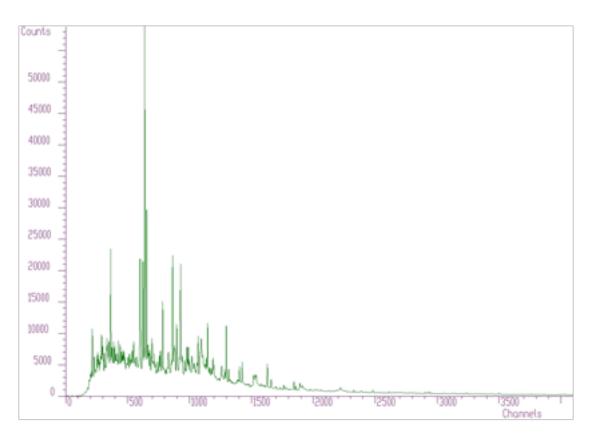


Figure 6.1: Spectrum with many peaks

In Figures. 6.2, 6.3, 6.4 we present this spectrum transformed using Haar, Walsh and Cosine transforms, respectively.

Haar transforms (Figure 6.2) creates clusters of data. These coefficients can be analyzed and then filtered, enhanced etc. On the other hand Walsh transform (Figure 6.3) concentrates the dominant components near to zero of the coordinate system. It is more suitable to process data of rectangular shape (e.g. in the field of digital signal processing). Finally Cosine transform concentrates in the best way the transform coefficients to the beginning of the coordinate system. From the point of view of the variance distribution it is sometimes called suboptimal. One can notice that approximately one half of the coefficients are negligible. This fact can be utilized to the compression purposes (in two or more dimensional data), filtering (smoothing) etc.

We have implemented several application functions utilizing the properties of the orthogonal transforms. Let us start with zonal filtration function. It has the form.

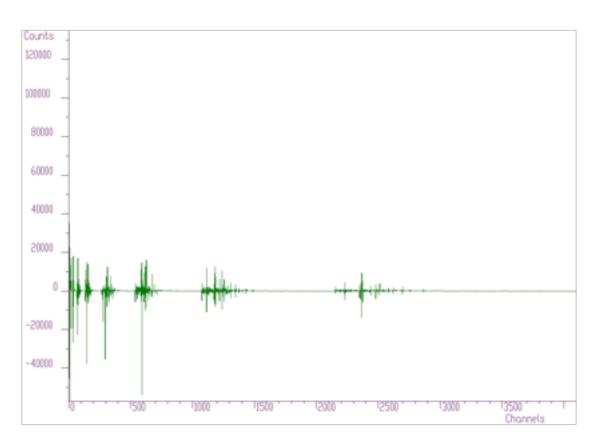


Figure 6.2: Spectrum transformed using Haar transform

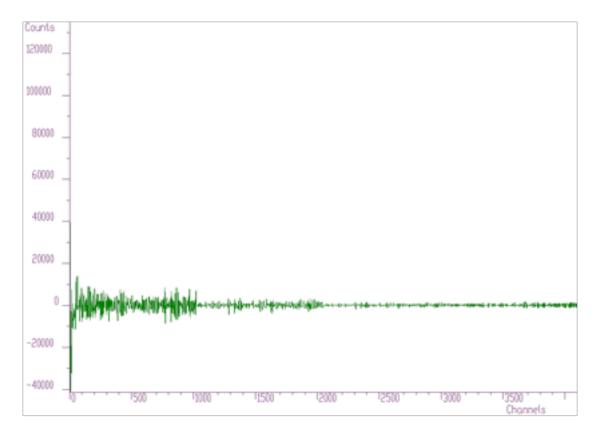


Figure 6.3: Spectrum transformed using Walsh transform

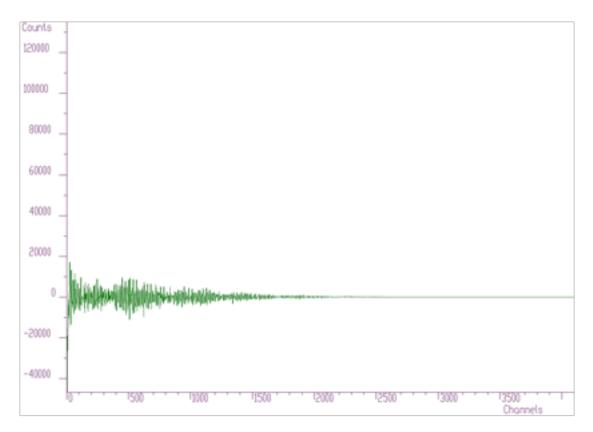


Figure 6.4: Spectrum transformed using Cosine transform

This function transforms the source spectrum. The calling program should fill in input parameters. Then it sets transformed coefficients in the given region (xmin, xmax) to the given filter_coeff and transforms it back Filtered data are written into dest spectrum.

- source pointer to the vector of source spectrum, its length should be size
- dest pointer to the vector of dest data, its length should be size
- **size** basic length of source and dest spectra
- type type of transform
 - TRANSFORM1_HAAR
 - TRANSFORM1_WALSH
 - TRANSFORM1_COS
 - TRANSFORM1 SIN
 - TRANSFORM1_FOURIER
 - TRANSFORM1_HARTLEY
 - TRANSFORM1_FOURIER_WALSH
 - TRANSFORM1_FOURIER_HAAR
 - TRANSFORM1_WALSH_HAAR
 - TRANSFORM1_COS_WALSH
 - TRANSFORM1_COS_HAAR
 - TRANSFORM1_SIN_WALSH
 - TRANSFORM1_SIN_HAAR
- degree applied only for mixed transforms

- **xmin** low limit of filtered region
- **xmax** high limit of filtered region
- filter_coeff value which is set in filtered region

An example of the filtration using Cosine transform is given in the Figure 6.5. It illustrates a part of the spectrum from Figure 6.1 and two spectra after filtration preserving 2048 coefficients and 1536 coefficients. One can observe very good fidelity of the overall shape of both spectra with the original data. However some distortion can be observed in details of the second spectrum after filtration preserving only 1536 coefficients. The useful information in the transform domain can be compressed into one half of the original space.

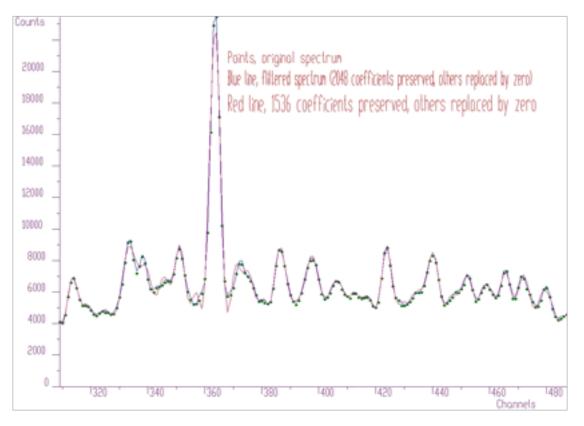


Figure 6.5: Filtration using Cosine transform

In the transform domain one can also enhance (multiply with the constant > 1) some regions. In this way one can change peak-to-background ratio. This function has the form

```
char *Enhance1(const float *source,
    float *dest,
    int size,
    int type,
    int degree,
    int xmin,
    int xmax,
    float enhance-coeff);
```

This function transforms the source spectrum. The calling program should fill in input parameters. Then it multiplies transformed coefficients in the given region (xmin, xmax) by the given enhance_coeff and transforms it back Processed data are written into dest spectrum.

- source pointer to the vector of source spectrum, its length should be size
- dest pointer to the vector of dest data, its length should be size
- size basic length of source and dest spectra
- type type of transform
 - TRANSFORM1_HAAR
 - TRANSFORM1_WALSH

- TRANSFORM1_COS
- TRANSFORM1_SIN
- TRANSFORM1_FOURIER
- TRANSFORM1_HARTLEY
- TRANSFORM1_FOURIER_WALSH
- TRANSFORM1_FOURIER_HAAR
- TRANSFORM1_WALSH_HAAR
- TRANSFORM1_COS_WALSH
- TRANSFORM1_COS_HAAR
- TRANSFORM1_SIN_WALSH
- TRANSFORM1_SIN_HAAR
- degree applied only for mixed transforms
- xmin low limit of filtered region
- xmax high limit of filtered region
- enhance_coeff value by which the filtered region is multiplied

An example of enhancement of the coefficients from region 380-800 by the constant 2 in the Cosine transform domain is given in the Figure 6.6. The determination of the region is a matter of analysis in the appropriate transform domain. We assumed that low frequency components are placed in the low coefficients. As it can be observed the enhancement changes the peak-to-background ratio.

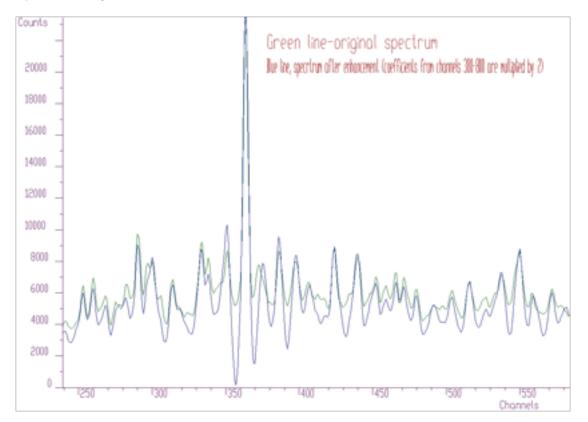


Figure 6.6: Enhancement of the coefficients from region 380-800 by the constant 2 in the Cosine transform domain

6.2 2-DIMENSIONAL SPECTRA

Analogously to 1-dimensional data we have implemented the transforms also for 2-dimensional data. Besides of the classic orthogonal transforms

- Haar
- Walsh
- Cos
- Sin
- Fourier

6.2. 2-DIMENSIONAL SPECTRA

- Hartley
- Fourier-Haar
- Fourier-Walsh
- Walsh-Haar
- Cos-Walsh
- Cos-Haar
- Sin-Walsh
- Sin-Haar

```
char *Transform2(const float **source,
        float **dest,
        int sizex,
        int sizey,
        int type,
        int direction,
        int degree);
```

This function transforms the source spectrum. The calling program should fill in input parameters. Transformed data are written into dest spectrum.

Function parameters:

- source pointer to the matrix of source spectrum, its size should be sizex*sizey except for inverse FOURIER, FOUR-WALSH, FOUR-HAAR transform. These need sizex*2*sizey length to supply real and imaginary coefficients.
- dest pointer to the matrix of destination data, its size should be sizex*sizey except for direct FOURIER, FOUR-WALSh, FOUR-HAAR. These need sizex*2*sizey length to store real and imaginary coefficients
- sizex, sizey basic dimensions of source and dest spectra
- **type** type of transform
 - TRANSFORM2_HAAR
 - TRANSFORM2 WALSH
 - TRANSFORM2 COS
 - TRANSFORM2 SIN
 - TRANSFORM2 FOURIER
 - TRANSFORM2 HARTLEY
 - TRANSFORM2 FOURIER WALSH
 - TRANSFORM2 FOURIER HAAR
 - TRANSFORM2 WALSH HAAR
 - TRANSFORM2_COS_WALSH
 - TRANSFORM2 COS HAAR
 - TRANSFORM2_SIN_WALSH
 - TRANSFORM2 SIN HAAR
- direction transform direction (forward, inverse)
- degree applies only for mixed transforms

An example of the 2-dimensional Cosine transform of data from Figure 5.6 is given in Figure 6.7. One can notice that the data are concentrated again around the beginning of the coordinate system. This allows to apply filtration, enhancement and compression techniques in the transform domain.

In some cases when the spectrum is smooth the cosine transforms are very efficient. In Figures 6.8, 6.9 we show original spectrum and transformed coefficients using Cosine transform, respectively.

Analogously to 1-dimensional case we have implemented also the functions for zonal filtration, Gauss filtration and enhancement. The zonal filtration function using classic transforms has the form

```
char *Filter2Zonal(const float **source,
        float **dest,
        int sizex,
        int sizey,
        int type,
```

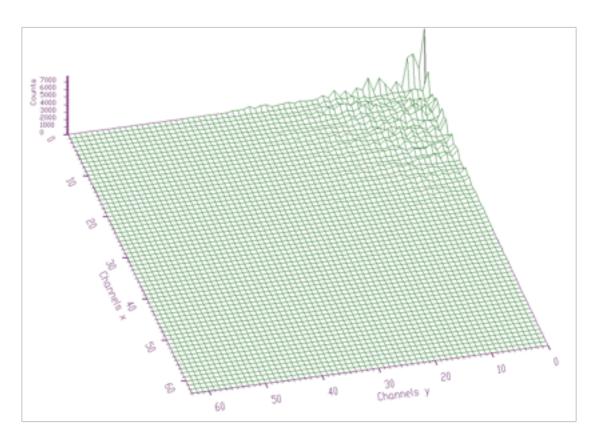


Figure 6.7: 2-dimensional Cosine transform of data from Figure 5.6

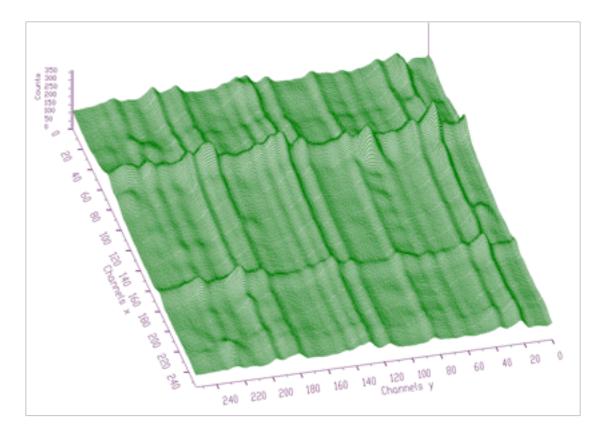


Figure 6.8: Original spectrum

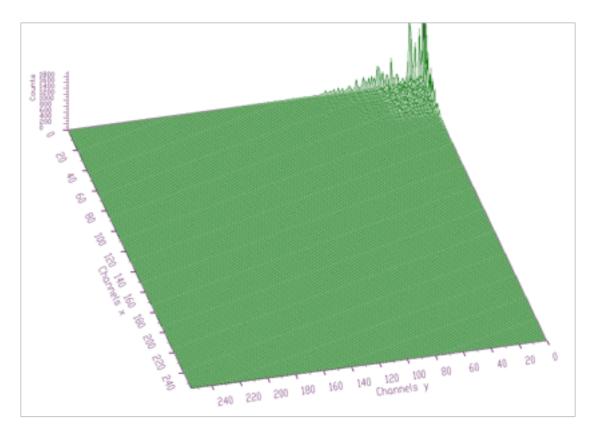


Figure 6.9: Transformed coefficients using Cosine transform

```
int degree,
int xmin,
int xmax,
int ymin,
int ymax,
float filter-coeff);
```

This function transforms the source spectrum. The calling program should fill in input parameters. Then it sets transformed coefficients in the given region to the given filter_coeff and transforms it back Filtered data are written into dest spectrum.

- source pointer to the matrix of source spectrum, its size should be sizex*sizey
- ${\tt dest}$ pointer to the matrix of destination data, its size should be sizex*sizey
- sizex, sizey basic dimensions of source and dest spectra
- type type of transform
 - TRANSFORM2 HAAR
 - TRANSFORM2_WALSH
 - TRANSFORM2_COS
 - TRANSFORM2 SIN
 - TRANSFORM2_FOURIER
 - TRANSFORM2 HARTLEY
 - TRANSFORM2 FOURIER WALSH
 - TRANSFORM2_FOURIER_HAAR
 - TRANSFORM2_WALSH_HAAR
 - TRANSFORM2_COS_WALSH
 - TRANSFORM2 COS HAAR
 - TRANSFORM2 SIN WALSH
 - TRANSFORM2_SIN_HAAR
- **degree** applies only for mixed transforms
- **xmin** low limit x of filtered region

- **xmax** high limit x of filtered region
- ymin low limit y of filtered region
- ymax high limit y of filtered region
- filter_coeff value which is set in filtered region

The enhancement function using transforms has the form

```
char *Enhance2(const float **source,
    float **dest,
    int sizex,
    int sizey,
    int type,
    int degree,
    int xmin,
    int xmax,
    int ymin,
    int ymax,
    float enhance-coeff);
```

This function transforms the source spectrum. The calling program should fill in input parameters. Then it multiplies transformed coefficients in the given region by the given enhance_coeff and transforms it back

- source pointer to the matrix of source spectrum, its size should be sizex*sizey
- ${\tt dest}$ pointer to the matrix of destination data, its size should be sizex*sizey
- $\verb+sizex, \verb+sizey+$ basic dimensions of source and dest spectra
- type type of transform
 - TRANSFORM2_HAAR
 - TRANSFORM2_WALSH
 - TRANSFORM2_COS
 - TRANSFORM2_SIN
 - TRANSFORM2_FOURIER
 - TRANSFORM2_HARTLEY
 - TRANSFORM2_FOURIER_WALSH
 - TRANSFORM2_FOURIER_HAAR
 - TRANSFORM2_WALSH_HAAR
 - TRANSFORM2_COS_WALSH
 - TRANSFORM2_COS_HAAR
 - TRANSFORM2_SIN_WALSH
 - TRANSFORM2_SIN_HAAR
- **degree** applies only for mixed transforms
- **xmin** low limit x of filtered region
- **xmax** high limit x of filtered region
- **ymin** low limit y of filtered region
- ymax high limit y of filtered region
- enhance-coeff value which is set in filtered region

Chapter 7

VISUALIZATION

7.1 1-DIMENSIONAL SPECTRA

The 1-dimensional visualization function displays spectrum (or part of it) on the Canvas of a form. Before calling the function one has to fill in one_dim_pic structure containing all parameters of the display. The function has the form

```
char *display1(struct one-dim-pic* p);
```

This function displays the source spectrum on Canvas. All parameters are grouped in one_dim_pic structure. Before calling display1 function the structure should be filled in and the address of one_dim_pic passed as parameter to display1 function. The meaning of appropriate parameters is apparent from description of one_dim_pic structure. The constants , which can be used for appropriate parameters are defined in procfunc.h header file.

```
struct one_dim_pic {
   float *source; // spectrum to be displayed
   TCanvas *Canvas; // Canvas where the spectrum will be displayed
   int size; // size of source spectrum
   int xmin; // x-starting channel of spectrum
   int xmax; // x-end channel of spectrum
   int ymin; // base counts
   int ymax; // count full scale
   int bx1; // position of picture on Canvas, min x
   int bx2; // position of picture on Canvas, max x
   int by1; // position of picture on Canvas, min y
   int by2; // position of picture on Canvas, max y
                        // spectrum display mode (points, polyline, bars, rainbow, steps, bezier)
   int display_mode;
                        // y scale (linear, log, sqrt)
   int y_scale;
   int levels;
                        // # of color levels for rainbow display mode, it does not apply
                        // for other display modes
   float rainbow1 step; // determines the first color component step for neighbouring
                        // color levels, applies only for rainbow display mode
   float rainbow2_step; // determines the second component color step for
                        // neighbouring color levels, applies only for rainbow display mode
   float rainbow3_step; // determines the third component color step for
                        // neighbouring color levels, applies only for rainbow display mode
   int color_alg; // applies only for rainbow display mode (rgb smooth algorithm, rgb
                  // modulo color component, cmy smooth algorithm, cmy modulo color
                  // component, cie smooth algorithm, cie modulo color component, yig
                  // smooth algorithm, yig modulo color component, hsv smooth
                  // algorithm, hsv modulo color component [15]
```

```
// applies only for bar display mode
   int bar thickness;
                                // (empty bars, full bars) applies only for bar display mode
   int bar_empty_flag;
                                // color of background of the picture
   int border_color;
   int full_border;
                                // decides whether background is painted
                                // decides whether the axes and rasters are shown
   int raster_en_dis;
                                // decides whether the rasters are drawn as long lines
   int raster_long;
                                // color of the rasters
   int raster_color;
   char *raster_description_x; // x axis description
   char *raster_description_y; // y axis description
   int pen_color; // color of spectrum
   int pen_dash; // style of pen
   int pen_width; // width of line
   int chanmark_style; // style of channel marks
   int chanmark_width; // width of channel marks
int chanmark_height; // height of channel marks
   int chanmark_en_dis; // decides whether the channel marks are shown
   int chanmark_color; // color of channel marks
   // auxiliary variables, transform coefficients, for internal use only
   double mx;
   double my;
   double px;
   double py;
   // auxiliary internal variables, working place
   double gbezx,gbezy;
   TPoint bz[4];
};
```

The examples using different display parameters are shown in the next few Figures

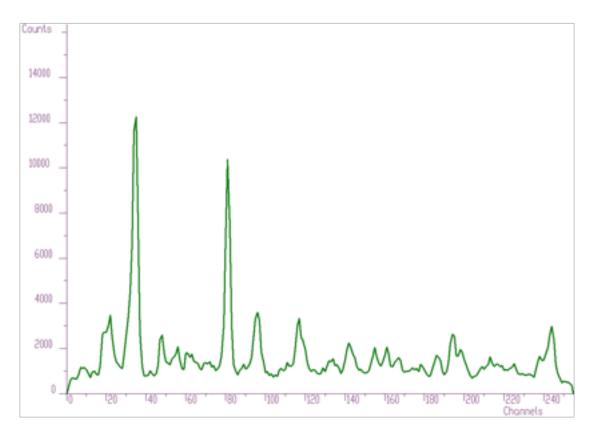


Figure 7.1: Display mode -polyline, width of pen=3

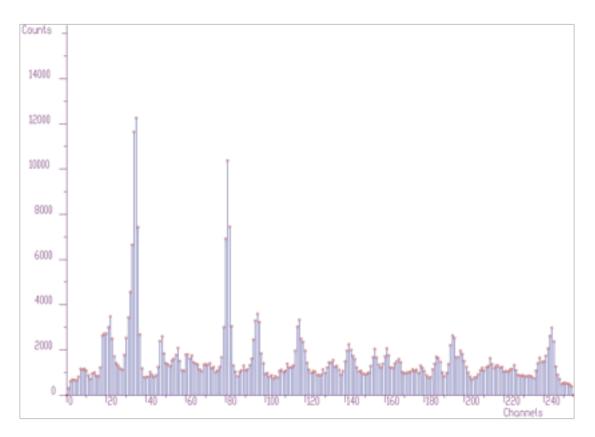


Figure 7.2: Display mode- bars, shown channel marks

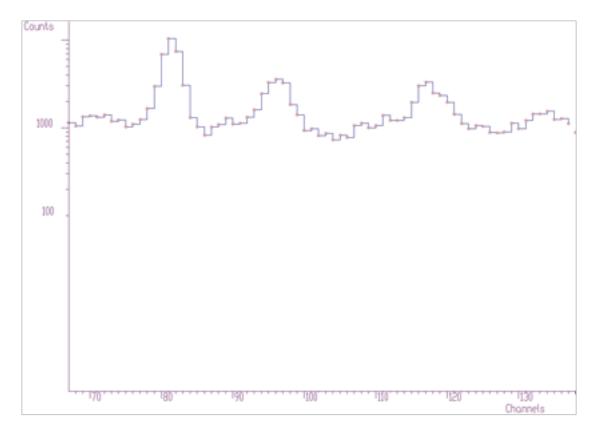


Figure 7.3: Display mode- steps, log scale, shown channel marks

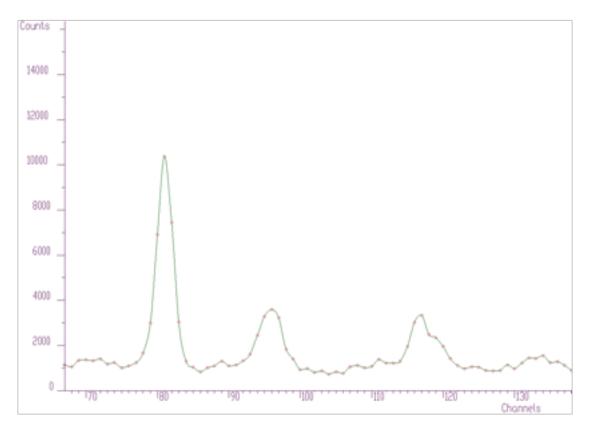


Figure 7.4: Display mode -Bezier curve interpolation, shown channel marks

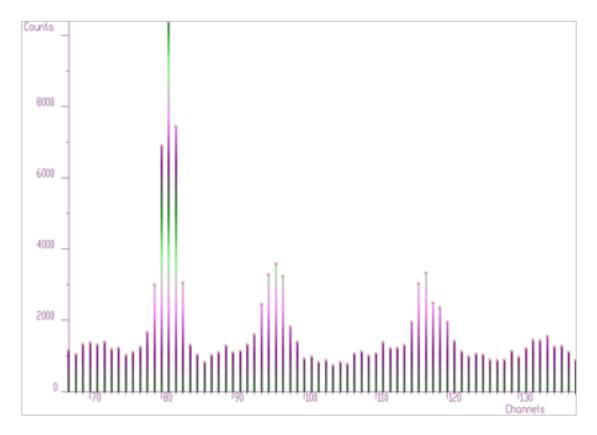


Figure 7.5: Display mode- rainbow bars, color algorithm (model) RGB, number of color levels=1024, pen width=3

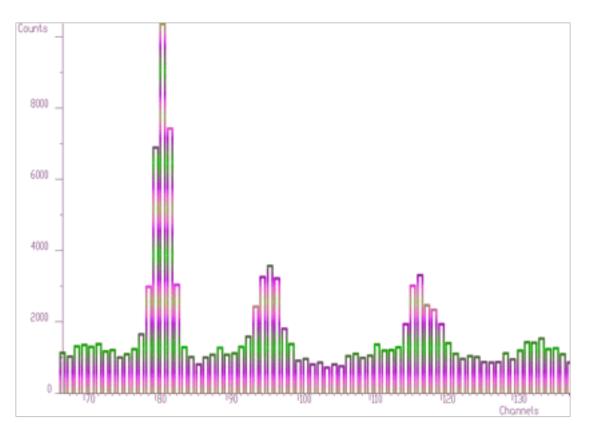


Figure 7.6: Display mode-empty bars, color algorithm YIQ, number of color levels 2048

7.2 2-DIMENSIONAL SPECTRA

The 2-dimensional visualization function displays spectrum (or part of it) on the Canvas of a form. Before calling the function one has to fill in two_dim_pic structure containing all parameters of the display. The function has the form

char *display2(struct two-dim-pic* p);

This function displays the source two dimensional spectrum on Canvas. All parameters are grouped in two_dim_pic structure. Before calling display2 function the structure should be filled in and the address of two_dim_pic passed as parameter to display2 function. The meaning of appropriate parameters is apparent from description of one_dim_pic structure. The constants , which can be used for appropriate parameters are defined in procfunc.h header file.

```
struct two_dim_pic {
```

<pre>float **source; // source spectrum to be displayed</pre>	
TCanvas *Canvas; // Canvas where the spectrum will be displayed	
<pre>int sizex; // x-size of source spectrum int sizey; // y-size of source spectrum int xmin; // x-starting channel of spectrum int xmax; // x-end channel of spectrum int ymin; // y-starting channel of spectrum int ymax; // y-end channel of spectrum int zmin; // base counts int zmax; // counts full scale int bx1; // position of picture on Canvas, min x int bx2; // position of picture on Canvas, max x int by1; // position of picture on Canvas, max y int by2; // position of picture on Canvas, max y int mode_group; // display mode algorithm group (simple modes- // PICTURE2_MODE_GROUP_SIMPLE, modes with shading // according to light-PICTURE2_MODE_GROUP_LIGHT, modes with // shading according to channels counts-</pre>	tħ

	// DICTUDED MODE (DOUD HEIGHT mades of combination of
	<pre>// PICTURE2_MODE_GROUP_HEIGHT, modes of combination of // shading according to light and to channels counts-</pre>
	// PICTURE2_MODE_GROUP_LIGHT_HEIGHT)
<pre>int display_mode;</pre>	// spectrum display mode (points, grid, contours, bars, x_lines,
int dispity_mode,	// y_lines, bars_x, bars_y, needles, surface, triangles)
<pre>int z_scale;</pre>	// z scale (linear, log, sqrt)
<pre>int nodesx;</pre>	// number of nodes in x dimension of grid
int nodesy;	// number of nodes in y dimension of grid
<pre>int count_reg;</pre>	// width between contours, applies only for contours display mode
int alfa;	// angles of display,alfa+beta must be less or equal to 90, alpha- angle
	// between base line of Canvas and left lower edge of picture picture
	// base plane
<pre>int beta;</pre>	// angle between base line of Canvas and right lower edge of picture base plane
<pre>int view_angle;</pre>	// rotation angle of the view, it can be 0, 90, 180, 270 degrees
<pre>int levels;</pre>	<pre>// # of color levels for rainbowed display modes, it does not apply for</pre>
flast meinhaut star.	// simple display modes algorithm group
<pre>iloat failbowi_step;</pre>	<pre>// determines the first component step for neighbouring color // levels, applies only for rainbowed display modes, it does not apply</pre>
	// for simple display modes algorithm group
float rainbow2 step:	// determines the second component step for neighbouring
,	// color levels, applies only for rainbowed display modes, it does not
	// apply for simple display modes algorithm group
<pre>float rainbow3_step;</pre>	// determines the third component step for neighbouring
	// color levels, applies only for rainbowed display modes, it does not
	// apply for simple display modes algorithm group
<pre>int color_alg;</pre>	// applies only for rainbowed display modes (rgb smooth algorithm,
	// rgb modulo color component, cmy smooth algorithm, cmy modulo
	// color component, cie smooth algorithm, cie modulo color component, // yiq smooth algorithm, yiq modulo color component, hsv smooth
	// algorithm, hsv modulo color component, it does not apply for simple
	// display modes algorithm group [15]
<pre>float l_h_weight;</pre>	// weight between shading according to fictive light source and
	// according to channels counts, applies only for
	// PICTURE2_MODE_GROUP_LIGHT_HEIGHT modes group
<pre>int xlight;</pre>	// x position of fictive light source, applies only for rainbowed display
int oliver	// modes with shading according to light
<pre>int ylight;</pre>	<pre>// y position of fictive light source, applies only for rainbowed display // modes with shading according to light</pre>
<pre>int zlight;</pre>	// z position of fictive light source, applies only for rainbowed display
int ziignt,	// modes with shading according to light
<pre>int shadow;</pre>	// determines whether shadow will be drawn (no shadow, shadow),
	// for rainbowed display modes with shading according to light
<pre>int shading;</pre>	// determines whether the picture will shaded, smoothed (no shading,
	// shading), for rainbowed display modes only
<pre>int bezier;</pre>	// determines Bezier interpolation (applies only for simple display
int handen selen.	<pre>// modes group for grid, x_lines, y_lines display modes) // acles of background of the misture</pre>
<pre>int border_color; int full_border;</pre>	// color of background of the picture // decides whether background is painted
<pre>int rull_border, int raster_en_dis;</pre>	
<pre>int raster_long;</pre>	// decides whether the rasters are drawn as long lines
<pre>int raster_color;</pre>	// color of the rasters
<pre>char *raster_descrip</pre>	otion_x; // x axis description
<pre>char *raster_descrip</pre>	<pre>ption_y; // y axis description</pre>
-	<pre>btion_z; // z axis description</pre>
<pre>int pen_color;</pre>	// color of spectrum
<pre>int pen_dash; int pen_width;</pre>	// style of pen
<pre>int pen_width; int charmark on dia;</pre>	// width of line
<pre>int chanmark_en_dis; int chanmark_style;</pre>	
int chanmark_width;	
<pre>int chanmark_height;</pre>	
<pre>int chanmark_color;</pre>	
<pre>int chanline_en_dis;</pre>	

```
// auxiliary variables, transformation coefficients for internal use only
   double kx;
   double ky;
   double mxx;
   double mxy;
   double myx;
   double myy;
   double txx;
   double txy;
   double tyx;
   double tyy;
   double tyz;
   double vx;
   double vy;
   double nu_sli;
   // auxiliary internal variables, working place
   double z,zeq,gbezx,gbezy,dxspline,dyspline;
   int xt,yt,xs,ys,xe,ye,priamka,z_preset_value;
   unsigned short obal[MAXIMUM_XSCREEN_RESOLUTION];
   unsigned short obal_cont[MAXIMUM_XSCREEN_RESOLUTION];
   TPoint bz[4];
};
```

The examples using different display parameters are shown in the next few Figures.

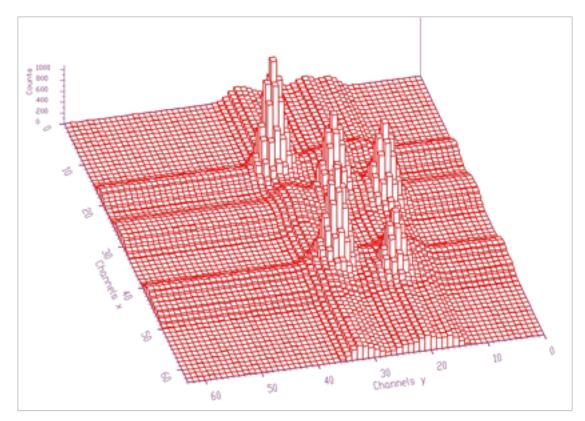


Figure 7.7: Display mode-bars, pen width=2

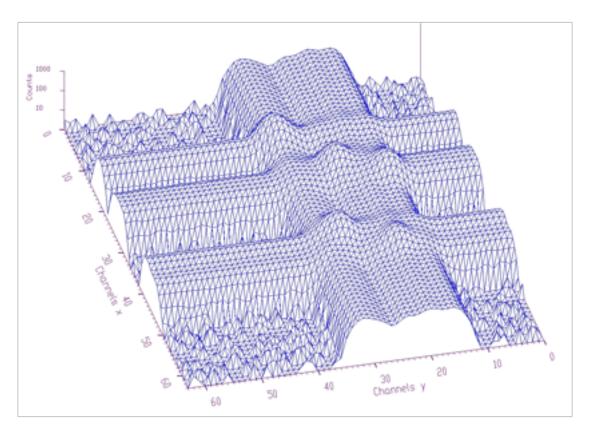


Figure 7.8: Display mode-triangles, log scale

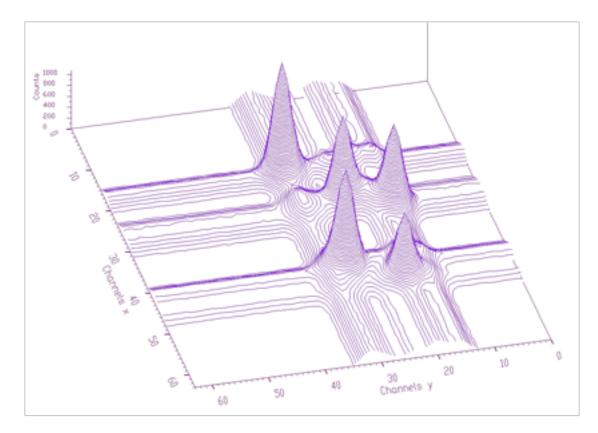


Figure 7.9: Display mode-contours

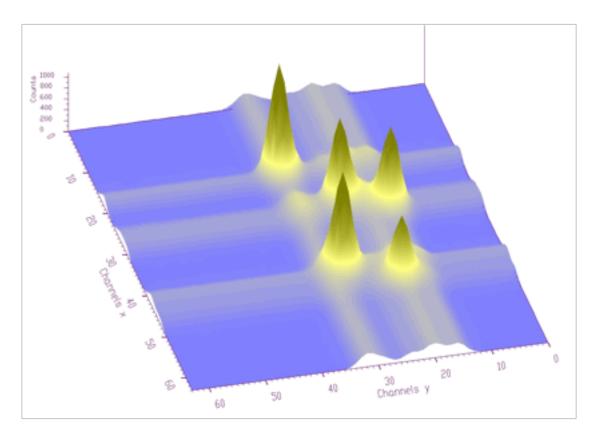


Figure 7.10: Display mode surface shading according to height

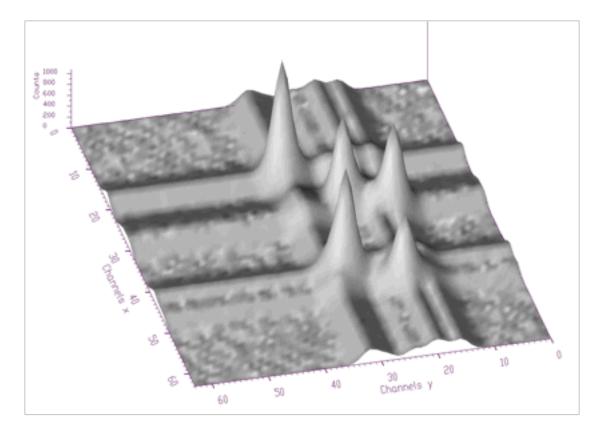


Figure 7.11: Display mode-surface shading according to light point

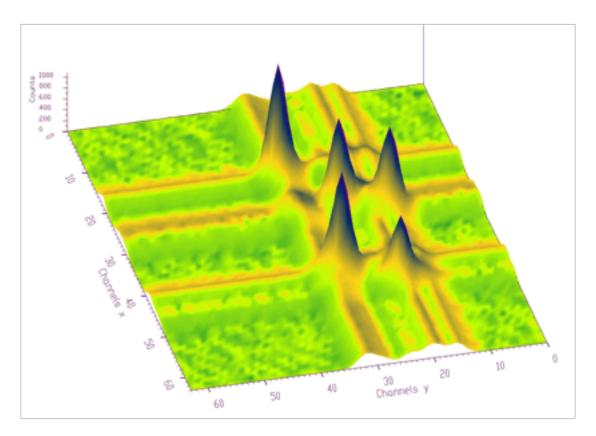


Figure 7.12: Display mode-surface shading according to height+light position with ratio 50:50, CMY color model

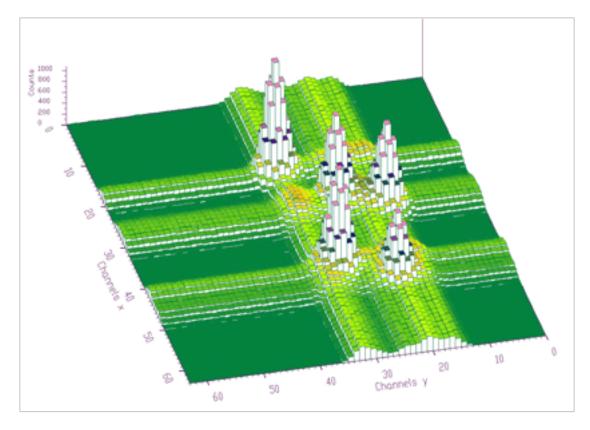


Figure 7.13: Display mode bars shaded according to height

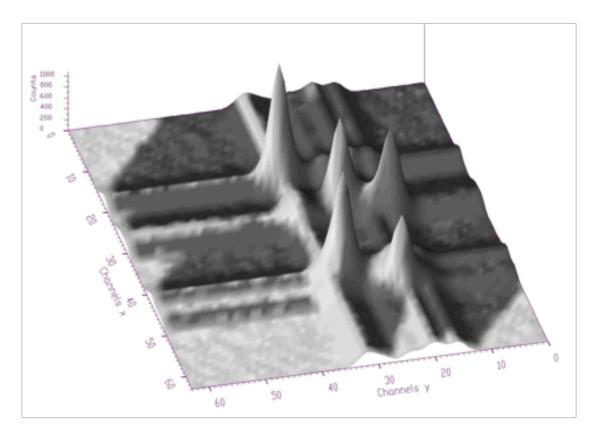


Figure 7.14: Display mode- surface shading according to light position with shadows

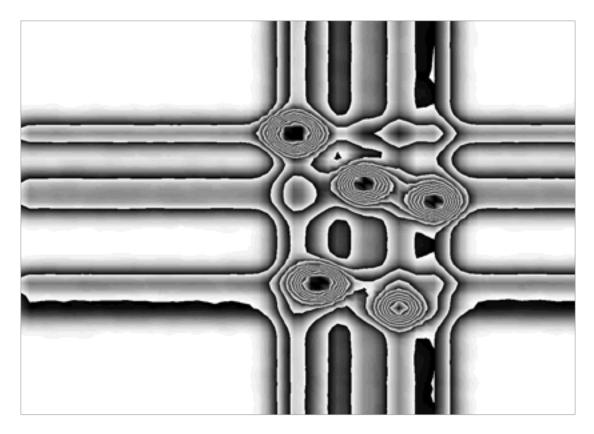


Figure 7.15: Display mode- surface shading according to height with 10 levels of contours

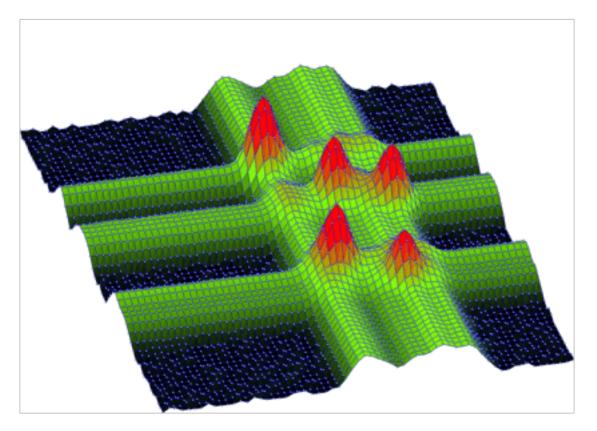


Figure 7.16: Display mode- surface shading according to height, sqrt scale, channel marks and lines shown

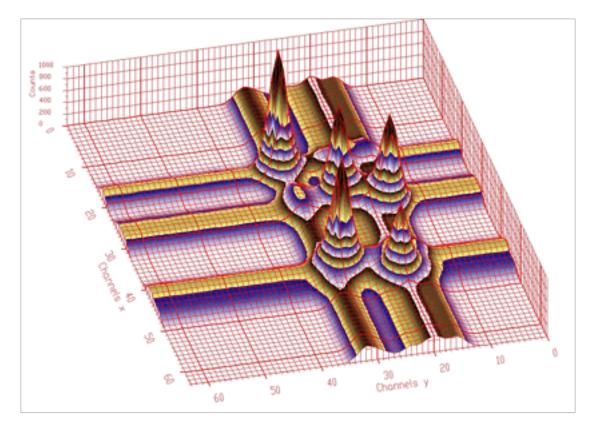


Figure 7.17: Display mode- surface shading according to height-contours, rasters allowing to localize interesting parts are shown.

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