GANIL

**A contextual image segmentation system using
a priori information for automatic data classification in
nuclear Physics.**

**A. Benkirane ⁽¹⁾, G. Auger ⁽¹⁾, D. Bloyet ⁽²⁾,
A. Chbihi ⁽¹⁾, E. Plagnol ⁽³⁾.**

**(1) Grand Accélérateur National d'Ions Lourds (GANIL)
Bd H. Becquerel BP 5027 14021 Caen cedex**

**(2) Institut des Sciences de la Matière et du Rayonnement Atomique (ISMRA)
/ Laboratoire d'Électronique et d'Instrumentation (LEI)
6, Bd du Maréchal Juin 14050 Caen Cedex**

**(3) Institut de Physique Nucléaire (IPN)
BP n° 1 91406 Orsay cedex**

Submitted to N.I.M.

GANIL P 94 20

A contextual image segmentation system using *a priori* information for automatic data classification in nuclear Physics.

**A. Benkirane ⁽¹⁾, G. Auger ⁽¹⁾, D. Bloyet ⁽²⁾,
A. Chbihi ⁽¹⁾, E. Plagnol ⁽³⁾.**

(1) Grand Accélérateur National d'Ions Lourds (GANIL)
Bd H. Becquerel BP 5027 14021 Caen cedex

(2) Institut des Sciences de la Matière et du Rayonnement Atomique (ISMRA)
/ Laboratoire d'Électronique et d'Instrumentation (LEI)
6, Bd du Maréchal Juin 14050 Caen Cedex

(3) Institut de Physique Nucléaire (IPN)
BP n° 1 91406 Orsay cedex

Abstract: This paper presents an original approach to solve an automatic data classification problem by means of image processing techniques. The classification is achieved using image segmentation techniques for extracting the meaningful classes. Two types of information are merged for this purpose: the information contained in experimental images and *a priori* information derived from underlying physics (and adapted to image segmentation problem). This data fusion is widely used at different stages of the segmentation process. This approach yields interesting results in terms of segmentation performances, even in very noisy cases. Satisfactory classification results are obtained in cases where more "classical" automatic data classification methods fail.

keywords: Automatic data classification, contextual image segmentation, *a priori* information, data fusion, optimal roof edge detector, automatic particle identification, (E,ΔE) spectra.

Section I : Introduction

Image segmentation approach is widely used in computer vision field, but can also be of great interest in many other fields where 2D representations (that can be considered as images) are used for data analysis. One of these is the nuclear physics field. Actually, usual first level analysis of nuclear physics experiments data use 2D representations (histograms) where data assemble into classes representing each a type of events. When visualised, these pictures contain clusters that are to be extracted to achieve a data classification.

The object of the present paper is to present a novel and efficient method, based on image segmentation techniques, to solve this classification problem in cases where "classical" clustering algorithms fail in finding satisfactory partitioning of the data.

The complexity of different steps of a segmentation process depends naturally on the type of images to be processed and on the S/N ratio. It also depends on the differentiation step efficiency against noise effects: Numerical differentiation of an image is actually an ill-posed problem [1]. Differentiation operation requires then the use of operators that have regularization properties ([1], [2] and [3]). Depending on the application, isotropic or directional operators are used. One of the most important parameters is the operator's scale. Witkin introduced in [4] a scale-space description of edge points position which describes the edge localization evolution through the scale axis. Multiresolution studies using this scale-space representation is proposed by Yuille and Poggio in [5] and [6]. The use of filters of different scale in human vision was at the origin of this multiresolution approach that uses multiscale filtering in computer vision ([7] and [8]).

Compared to a general approach, our segmentation procedure uses a priori information (derived from physics processes underlying to the 2D representations). This data fusion permits to avoid a multiresolution approach as the a priori information are used to determine smoothing and differentiating operator's parameters. It is at the origin of very satisfactory results in terms of differentiation performances.

We present in section II the origin of our images, and briefly describe the context of our work (experimental device and data types). The second part of this section deals with "classical" clustering methods inadequacy in our application case.

In section III, we describe the a priori information extraction and customization to image segmentation context. Their use in different steps of the segmentation process (directional smoothing of the image, differentiation operator's scale adjustment...) is then exposed.

We discuss in section IV the obtained results when applying our contextual image segmentation system to different 2D histograms to achieve data classification in different situations: noisy images, large number of classes,...

Section II : Experimental context and image type

The study of nuclear multifragmentation obtained by heavy ion nuclear reactions has known a considerable development in recent years. In the intermediate energy range ($10 \leq E_{lab} \leq 100$ MeV/A) these multifragmentation processes are observed for the most violent and central collisions. One of the particularities of these reactions is to produce a great variety of particles and nuclei : large multiplicities (≥ 50) are observed and the nature and energy of these products cover a considerable dynamic range.

As it is believed that a better understanding of this physics will be reached if a precise detection is achieved, the collection and identification of these products is of primary importance and not surprisingly technically very difficult. In recent years, the improvements in detector technics, electronic treatment of signals and computer power have led to the construction of extremely efficient devices that allow an almost complete detection and identification of these products. They are labelled 4π detectors because they cover most (90%) of the geometric angular range accessible to the nuclei.

The INDRA (Identification de Noyaux et Détection avec Résolutions Accrues) detector, constructed by a collaboration of four french laboratories (DAPNIA-Saclay, GANIL-Caen, IPN-Orsay and LPC-Caen) and operating at the GANIL facility is an example of one of the latest and most sophisticated of these detectors. A detailed description of the detector is given in [9] and [10].

However, correlated with the capability of recording most of the information available is the very complex problem of analysing it.

In the case of INDRA, the particles and nuclei are detected and identified by the energy losses that they deposit when penetrating through the detection cells. A typical detection cell (figure 2) is made of several sensitive layers (ionization chambers, Silicon detector and Cesium iodide scintillator) associated to their corresponding electronics. The energy losses deposited are converted into digital information and stored.

To identify these products, 2D histograms representing the energy losses of particles that have penetrated two different layers of a given cell are used. Each particle or nuclei will be located on the histogram at a point that depends on its nature (mass and charge) and on its velocity. A matrix (image) can be filled by thousands of such events, some of them cumulating at the same location. With sufficient statistics, a picture of ridges (Z-lines) and valleys will appear (fig 2 and 3), each ridge being associated to a given specie of nuclei (mostly determined by its charge Z). As the number of such matrices for a typical measurement will be itself in the thousands, the problem is therefore to devise an unsupervised method to identify all of the detected particles.

The identification of the particles in (E, ΔE) spectra is therefore a data classification problem. It consists in recognizing the particles that belong to the same class, and affecting to each of the so obtained classes an identification number that corresponds to the charge Z of its particles. As

made clear in figure 3, the classes identification number increases from down to up beginning from light particles $Z=1$ (protons, deuterons and tritons), then $Z=2$ (alpha particles) and so on.

This classification was till now achieved manually: using interactive software, human operators extract, for each spectrum, contour-points corresponding to each Z-line and affect to the so obtained class the corresponding identification number.

No unsupervised methods have been proposed in literature to resolve this problem of data classification in $(E, \Delta E)$ spectra, mainly because the number of spectra to be processed did not justify such investigations in the past. As we have seen, this is no more true with new generation multidetectors.

Some classical data classification methods

Before deciding on the edge detection techniques to extract Z-lines on $(E, \Delta E)$ spectra, we have first examined more “classical” data classification methods to group in the same class particles with identical charge (Z).

The “valley seeking” method was introduced by Koontz in [11], and consists in iterative minimization of a clustering criteria J defined as a classification error for a given partition of the set E of data :

$$J = \sum_{i=1}^N \sum_{j=1}^N f(X_i, X_j) [d_{\omega}(\omega_i, \omega_j) - d_X(X_i, X_j)]^2$$

$$i, j = 1, \dots, N$$

where N is the number of vectors to be classified: $N = \text{card}(E)$, X_i is an element of E belonging to the class ω_i , d_X is the distance between X_i and X_j , d_{ω} is a distance between ω_i and ω_j (euclidean distance between the class centers for example), f is a weighting function.

This method cannot be used in an unsupervised context when a large variety of spectra are to be processed as the iteration process has to be stopped when the “correct” classification is reached : indeed, a trivial solution that minimizes J is the configuration that corresponds to a unique class containing all the data set. In addition, any gathering of two or more classes into a unique one minimizes J . This method is then more adapted to the case of a few number of equivalent classes. It cannot be efficient when a large number of both dense and sparse classes are to be extracted.

Another automatic data classification method is the one proposed by Diday in [12]: “Dynamic clusters method”. The data are iteratively grouped into classes characterized each by its center. The class centers are recalculated at each iteration step. This method failed in finding correct classifications because it uses a distance that cannot be defined correctly in our case. This distance should be defined so as a data point is nearer to the center of its class than to the center of any other class. The shape of our classes justifies the inability of this method to yield the desired classification. It is indeed difficult, in our case, to find a definition of distance that verifies the above mentioned criteria.

A comparison of some iterative classification methods and results of their application to real data sets can be found in [13] and [14].

All these methods imply the definition of a metric. The distance that is used in the classification algorithms is a very important parameter and is difficult to define correctly in some applications. This is true in the case of our classes shapes. The large number of classes to be extracted and the important variance of the number of events in each class may induce an undesired merging of two or more close (in the sense of the adopted metric) classes.

These iterative clustering methods do not yield acceptable solutions for our classification problem. We shall adopt in the following a different approach that will try to reproduce the human operator's methodology. It consists in:

- extracting pixels in the $(E, \Delta E)$ pictures that correspond to the line centers (or ridges) that we will call edge points (or edge pixels).
- regrouping the edge points that belong to the same Z-line and attribute an identification number corresponding to the charge Z of the particles that this line represents.
- affecting each data point to the nearest extracted Z-line, thus achieving the data classification.

Before presenting this method, let us briefly list some characteristics of our images and some practical restrictions and requirements :

- The $(E, \Delta E)$ images may contain a few or a large number of classes depending on the nuclear collisions studied (up to $Z=60$ or even more!).
- The statistics of a spectra (i.e. data repartition) is physics dependent and may concern any energy range on E and ΔE axis.
- Physicists will want to identify with precision the maximum amount of data (particles) present on each image. This implies the extraction of all the Z-lines of a spectrum, including those corresponding to low statistics.
- Because of the large number of images to be processed, an unsupervised particle identification method is required.

Section III Image segmentation for Z-lines extraction using a priori information.

We first describe in this section the a priori information corresponding to the physics processes underlying to $(E, \Delta E)$ histograms and their customization to our picture segmentation problem. Smoothing and differentiation steps with filters parameters adaptation in accordance with these a priori information are then presented. The so obtained edge points chaining, and the Z-lines numbering are exposed in the last part of this section.

III.a A priori information on $(E, \Delta E)$ spectra:

The theoretical study of the penetration of matter by particles and nuclei was initiated by H. Bethe in the 1930's [15]. This work led to a modelisation of these processes which depend on a number of parameters that are not well known in most practical cases. Similarly, this theory is formulated in terms of physical quantities which are not determined at this initial step of the analysis, as for example the velocity of the detected ion. Thus, concerning the $(E, \Delta E)$ spectra, it does not allow for a direct identification of the particles.

Numerous studies and measurements of experimental energy losses have also been performed and have led to a number of stopping power tables that can be found in the literature ([16], [17], [18],...). These tables give an approximation of the energy (In MeV) lost by a particle crossing some material, assuming that the particle's charge and initial energy are known, as well as the material's nature and thickness. Here Again, a direct use of these tables for the particle identification tool cannot be done. Actually, stopping power tables precision is nearly 5%. In addition, calculated Z-lines and measured ones (on $(E, \Delta E)$ spectra) cannot match when superposed because of the non-linear behaviour of CsI detectors, whose calibration function depends not only on the energy range, but on the particle's charge Z as well [19]. The error in energy losses estimation, that depends on Z and E (i.e on the considered region of $(E, \Delta E)$ spectra), is often over 20%.

To summarize, the physics underlying to $(E, \Delta E)$ spectra cannot yield a Z-lines generation that is precise enough for the identification of experimental data. We present in the following a picture segmentation approach for extracting the Z-lines on $(E, \Delta E)$ spectra. However, we do think that the use of a general segmentation system is not the best solution in our context. Actually, as a priori information on images are available, it's worth using them to derive a more efficient contextual segmentation system.

A priori information extraction:

The aim is to deduce, from existing stopping power tables, information concerning $(E, \Delta E)$ pictures that can be used in our context. Two kind of information are important for this purpose:

- Z-lines inter-distances
- Z-lines slopes

Actually, a large number of the Z-lines on the $(E, \Delta E)$ spectra may be very noisy as soon as the corresponding particles are produced in limited numbers by the collision process. Precise detection of Z-lines then implies a prefiltering (smoothing) of these $(E, \Delta E)$ images. Instead of using a gaussian symmetric filter which would introduce a blurring effect that decreases the resolution, a directional smoothing can be achieved if information about the slopes of the Z-lines are available, resulting in an improvement of the S/N ratio. In addition, Z-lines inter-distances vary significantly depending on the considered region of the $(E, \Delta E)$ spectrum. The smoothing scale can be adapted in accordance with the Z-lines inter-distances information.

During the differentiation operation, an important parameter is the filter's scale. In the same way, a priori information can be a help at this step.

In practice, for a given $(E, \Delta E)$ spectrum, E and ΔE values are in coder's channels while the spectrum may concern any energy range (depending on the system under analysis and the detection angle). To use efficiently the a priori information whatever is the energy range, an approximate calibration of E and ΔE axis is required. Actually, once E and ΔE values (that characterize the currently processed pixel) are converted in MeV, Z-lines inter-distance and slope at that pixel can be obtained from some kind of distances and slopes tables that we describe hereunder.

The information we are interested in are extracted from the stopping power tables in the following way: for a given value of E in MeV, we calculate an approximate value of Z-lines slopes ($Z=1,2,3,\dots$) as a function of the ΔE variable. Discrete slopes values, as presented on figure 4, are thus obtained and fitted by a simple function. The same method is repeated for different values of E , scanning all the energy range that is accessible at GANIL. For non tabled E values, a linear interpolation of the slopes corresponding to the two nearest tabled values is used. This was found precise enough for our method as Z-lines slopes evolves slowly and often monotonously.

This allows, when processing the picture, to access a fast and sufficiently precise estimation of the Z-line slope at any current pixel, corresponding to a Z-line or not (automatic $(E, \Delta E)$ spectra processing assumes blind processing where a pixel is only characterized by E and ΔE values that are converted in MeV using the approximate calibrations values).

An identical procedure is performed to construct tables that give, for any given values of E and ΔE in MeV, an approximation of local Z-lines inter-distances (figure 4). This consists as before in determining a function that approximates distance evolution versus ΔE for a given value of E (E axis is once more sampled in $[0,5]$ GeV interval, and linear interpolation is used for non tabled values).

It is important to notice that unlike the case of direct use of stopping power tables for Z-lines generation, an error up to 15% in E and ΔE estimations is acceptable, as this estimation is simply used as a landmark that permits to make tail of the region under analysis, and then estimate its characteristics. These characteristics (Z-lines inter-distances and slopes) evolve slowly enough to afford such an error in the calibration values.

III.b Image smoothing and differentiation:

As can be seen in the $(E, \Delta E)$ spectra examples, some Z-lines can be very noisy when they correspond to poor statistics. We will use edge detection technics for Z-lines points extraction. This consists in an image differentiation, which is well known to be an ill posed problem ([1] and [3]) because of its lack of robustness against noise. Torre tackles in [1] the problem of image differentiation, and shows that it requires a priori filtering step to regularize the differentiation. Minimum uncertainty filters are the most appropriate for this step as they optimize a trade-off between

regularizing properties and computation efficiency (the gaussian filter is an example of minimum uncertainty filters).

We will use in our application a 2D filter for the filtering step, while the differentiation step will be achieved using 1D edge detectors.

smoothing

This first step is implemented to achieve two main goals:

- smoothing the image “intensity”. This facilitates the differentiation step since it increases the signal to noise (S/N) ratio as will be seen later.
- extrapolating the Z-lines at the distribution ends. This is useful to extract correctly the Z-lines in that regions where the statistics are poor, but where it is important for physicists to identify the corresponding data (particles).

We see here the importance of a priori information that will be used to derive non symmetrical filters (it is known that convoluting the image with symmetrical filters decreases the resolution). The image is then convolved with a spatial dependent filter in accordance with the analyzed region characteristics : at the current pixel, E and ΔE are estimated in MeV using the approximate calibration values, and the Z-lines slopes and distances are estimated (as previously described). This allows us to derive the mask that is to be used to convolve the image. This operation is repeated at each of the 512x512 pixels of the image.

An example of such a mask is given in figure 5, where ' θ ' and ' a ', as well as the mask dimension, are adapted to the local characteristics of the Z-lines given by the tables. This avoids a too large smoothing that can result in Z-lines merging, when these are too close to each other in the original (E, ΔE) spectra.

The 512x512 image may concern any energy range for E and ΔE axis, depending on the axis scales (E axis may concern a [0,500] MeV or a [0,5] GeV energy range for example, depending on the system under analysis). To determine the characteristics of the mask to be used at any current pixel, whatever the scale of the E and ΔE axis, it is necessary to use the calibration values

Using masks such as the one of figure 5 introduces implicit averaging of the image intensity mainly along the Z-line direction rather than across it. Its direction, its dimension and its width are recalculated at each pixel so that it lies in the Z-lines direction and that it does not include more than one Z-line at a time for the current pixel.

We could certainly use directional gaussian filters (whose direction and dimensions would be adapted locally in the same way as before), since they correspond to minimal uncertainty filters as mentioned before. We chose however to use support limited filters which offer more interesting computation performances (no multiplication is needed) even if their regularization performances are not as good. Nalwa explains informally in [20] that such unweighted averaging yields to better S/N

ratio than a gaussian filter. It is possible here to use such filters because the differentiation step will use optimal edge detectors that optimize the detection-localization trade-off.

One can also see the smoothing step as an adapted filtering strategy, just as when a unique shape is to be extracted in a noisy image, the matched mask to be used is the shape itself. we use here the same idea, but including the fact that the shape to be found changes at each pixel.

Figure 6 shows an example of such a smoothing procedure, other results can be found in section IV.

differentiation

In our application, we need a precise localization of the edge points as the extracted Z-lines are to be used for particle identification. Extracted Z-lines must then be at the center of the cloud of points that it represents. We also need a good detection performance as we need to detect Z-lines with low statistics.

In addition, some particularities of $(E, \Delta E)$ images are to be taken into account:

- No angle detection is needed as the Z-lines do never cross each other.
- Z-lines scales are different in a same image, Some are thin and close to each other, and others wide and are more distant.
- The intensity $I(x,y)$ of the picture is often very noisy, as it corresponds to low statistics Z-lines. The pixels weight in that regions is often 0, 1 or 2 and seldom more. It is then the points density that permits the human vision to distinguish Z-lines, and not the intensity function $I(x,y)$. This is one of the reasons of our prefiltering step, since it yields a smoother intensity function that can be more efficiently differentiated (lack of robustness of differentiation operation against noise).

Efficient extraction of edge points in a given image needs the use of appropriate tools that depend on edge characteristics (edge type and scale). We are interested here in extracting roof shaped edges. Second derivative of a roof edge has a maximum at the edge position. We will use then a second derivative operator for this purpose.

The filtering step previously described corresponds to a first regularization of the differentiation. As support limited filters that maximize the detection criteria (increasing S/N ratio is considered in [2] as a detection performances increasing), but don't have good enough regularization performances, have been used, it is worth using for this differentiation step filters that offer good localization performances.

Many authors suggest optimal edge detectors for a given edge in the sense of some criteria that they defined, which criteria are supposed to ensure "good" differentiation quality. Canny used in [2] and [21] a detection-localization criteria to derive optimal edge detectors, depending on the edge shape.

Three performance criteria were used by Canny:

- ➡ Good detection of the edge points that he considers equivalent to signal-to-noise ratio maximization.
- ➡ Good localization, i.e. the detected edge should be as close as possible to the center of the real edge.
- ➡ Only one response to a single edge.

Numerical optimisation of a composite criterion derived from the mathematical form of the ones mentioned above yields optimal edge detectors:

- The first derivative of a gaussian is a good approximation of step edge optimal detector.
- The laplacien of Gaussian (LoG) approximates well the roof edge optimal detector.

A Z-line cross section is close enough to a roof shape. Using the corresponding optimal edge detectors should yield satisfactory performances in detection and localization. Canny's roof edge detector (LoG) that optimises detection-localization trade-off will then be used here for the differentiation.

$$LoG: \quad f(x) = A \left(1 - \frac{x^2}{\sigma^2} \right) \exp \left(-\frac{x^2}{\sigma^2} \right)$$

In literature, 2D differentiation is achieved, when possible, using separable filters. This yields important processing time saving as the 2D filtering corresponds then to two 1D convolution operations.

Each 1D differentiation in a given direction might be accompanied by a projection operation in the orthogonal direction. The projection function is a smoothing filter. Canny [2] uses this kind of filters to derive directional filters for step edges (he uses a nearly rectangular projection function). In a different manner, one can note that Spacek [22] uses for picture differentiation 1D filters that lie in a direction that is orthogonal to the edge direction without using projection functions, while Nalwa [20] prefers, as mentioned above, rectangular projection function that he considers more efficient in terms of S/N ratio improvement.

These remarks will allow us to define the following approach for (E,ΔE) spectra differentiation:

- In the general case where no a priori information is available on the edges to be detected, the smoothing step is achieved using a 2D symmetric filter (that is well known to give decrease in resolution). Using a priori information as suggested, makes it possible to use directional smoothing filters that not only lead to a first smoothing of the intensity function $I(x,y)$ (and then a preliminary regularization of the differentiation), but also to significant increase in the S/N ratio as well.

This can also be considered as a projection operation where the projection function is adapted to the context of the current pixel. The rectangular projection function's orientation is

consistent with the Z-line orientation, while its width depends on the distance between two adjacent Z-lines at that pixel.

- A 2D differentiation permits to determine the edge position and its orientation. As we consider the orientation as an a priori information, the edge position extraction may be achieved using a 1D differentiation operation in a direction that is non collinear to the edge orientation (ideally orthogonal but not necessarily).

We have introduced the optimal edge detector that will be used for roof edge detection. We will see here the importance of its width to ensure detection-localization trade-off optimality.

Smearing of contours positions can actually be observed when operators with a too large width are used ([23] in step edge contours case). In the other hand, figure 8 shows a multiple response (maxima in the output signal) to a single noisy roof edge when the detector's scale is too small in comparison with the edge scale. The scale of the detector must then fit the edge scale. Huertas explains through some examples in [24] the influence of the LoG filter's width in edge points localization accuracy.

We then see here once more the help that can offer the a priori information through the distance tables presented before. As we do not know Z-line widths precisely⁽¹⁾, we approximate it as a portion of Z-lines inter-distance (a third or quarter, for example). We intentionally slightly underestimate the Z-lines real width. This is done to favour localization in the differentiation step; detection performance had already been improved (in the sense of Canny's criteria) by the directional smoothing which enhances the S/N ratio.

The differentiation is then achieved by convolving each column (1 pixel thin) of the $(E, \Delta E)$ smoothed image by a dynamically rescaled LoG filter at each pixel, the filter is recalculated according to the Z-lines inter-distance information before the differentiation is achieved.

An example of such an operation result is presented in figure 9.

If the smoothing and differentiation steps are not assisted by a priori information (gaussian symmetric smoothing filter and constant scale of the LoG differentiation filter), multiple responses to a single noisy edge are obtained when the smoothing and differentiation scales are too thin. In this case, broad Z-lines cannot be extracted correctly (figure 9.a). In the other hand, if the constant scale is adapted to broad Z-lines, the too large smoothing scale leads to the merging of two or more peaks (edge points) into one. Thin Z-lines are then not detected correctly (figure 9.b). This shows that the right approach is to adapt each step (smoothing and differentiation) to local characteristics of the edges.

In addition, when a directional smoothing is performed, the S/N ratio is significantly improved, yielding a satisfactory extraction of Z-lines with low statistics (High Z-lines in figure 9 to compare to those of figure 8).

(1) Z-line width cannot be known precisely as it depends on a lot of parameters (produced masses for a given isotope, energy and angular straggling, detectors resolution, electronic data acquisition device resolution...).

This gain in detection-localisation performances yields a nearly noise free edge points image in regions where Z-lines are perceptible. This facilitates significantly the following steps (chaining and numbering), especially in cases as those of figures 11 and 12 that contain a large number of Z-lines with low statistics.

III.c Z-lines extraction:

Thresholding:

One can easily understand that cut off points on $(E, \Delta E)$ spectra can also lead to the detection of edge points that should not be kept. The value of the response of LoG filter to such points is much lower than the one obtained for a real edge point. A thresholding is then necessary to eliminate such undesired edge points.

The adaptation of the smoothing and differentiation steps to local characteristics permitted to avoid detecting false edge points in regions of the image where Z-lines are visible (figure 6 shows an example of non thresholded differentiated image). However, the necessity of thresholding can be established in cases where some regions of the processed spectrum contain too few statistics that no Z-line can be observed (as some regions of the spectra of figures 11 and 12). These regions would naturally contain false edge points if no thresholding is applied.

We have chosen to use a constant threshold that has been fixed experimentally. We recall that during the smoothing step, the averaging is achieved on a region whose dimensions depend on the Z-lines characteristics locally (small region for thin Z-lines and bigger region for broad ones). Adopting a constant threshold in the edge detector's output is then equivalent to requiring a minimum number of particles in a region whose surface depends on Z-lines characteristics locally.

Thresholded edge points obtained after the differentiation step are only characterized by their co-ordinates but are not yet classified as belonging to a Z-line. The following steps are then needed to solve our classification problem:

- An edge points chaining step which will gather the edge points belonging to the same Z-line.
- A Z-lines numbering step which consists in giving to each Z-line an identification number, representing the charge Z of the particles.

After these two steps, it is often interesting to fit the edge points of each Z-line with an analytical "identification function" that will not only save memory space (thousands of spectra are concerned in the case of INDRA) but will also allow, if conveniently chosen, to extrapolate to regions where extremely small statistics are found. Such functions, as suggested by Steckmeyer [25] are described in Appendix 1.

Chaining

Chaining points that belong to the same contour in differentiated pictures is in general a complex problem. This results from different problems which are found when a scene, texture, indoor or biomedical image is processed (noisy differentiated image, different sorts of contours to be extracted, a few or no a priori information...). This step is much easier to achieve here as, in $(E, \Delta E)$ images, one knows the kind of contours to be extracted. The chaining is also easier because of the differentiation quality that is obtained from the adaptation of the smoothing and the differentiation procedures to the local characteristics of the image contours.

The chaining can then be easily achieved as follows:
the $(E, \Delta E)$ image is scanned column by column. All the edge points of the first column yield new classes (or lists) generation. The chaining is then continued as follows:

➡ Step i :

- if a point from column i does not belong to a class, a new class is generated.
- a neighbourhood region is delimited for each edge point of the i^{th} column (the a priori information are taken into account for determining the orientation and dimensions of this region).
- an edge point of the i^{th} column transmits its class number to the edge point of the $(i+1)^{\text{th}}$ column contained in its neighbourhood region.

➡ go to the $(i+1)^{\text{th}}$ step.

These three very simple rules, repeated at each step, allow the realization of an initial chaining. It is usually necessary to take into account a set of other simple rules that permits to manage atypical situations (multiple edge points of the $(i+1)^{\text{th}}$ column in the neighbourhood region of a unique edge point from column i, for example).

Numbering:

This first classification is a preliminary numbering of the Z-lines in the order of their appearance when the image is scanned by column. However, when a particular Z-line is discontinuous, usually because of low statistics, this step will not lead to the gathering of all the points of this Z-line into the same list. The numbering step will then correct this effect. It, indeed, assigns the same class number to two different classes stemming from the chaining step and representing the same Z-line.

A reference, that can either be extracted automatically (as its statistics is always much higher than the one of the following Z-lines) or given by an independent procedure, is the α particles Z-line ($Z=2$). It is used to initialize the numbering procedure. The numbering is then achieved Z-line by Z-line as follows:

Let α particles Z-line be the reference with identification number $Z=2$

➡ Step i:

- for any edge point A_j of the reference $Z=Z_i$
if an edge point A_{j+1} of the same column is at a “reasonable” distance of A_j , the whole class (obtained from chaining) to which A_{j+1} belongs is renumbered Z_i+1 .
- the new reference is the Z-line Z_i+1 .

➡ go to step (i+1).

By “reasonable” distance, we mean a distance that is consistent with the distance tables previously described (we tolerated an error up to 30% in our algorithm).

Once again, some additional simple rules are necessary to manage conflictual situations.

We summarize by saying that the chaining and numbering steps are complementary. The chaining is a first gathering of the edge points belonging to the same Z-line, but can yield in some situations several lists for a unique Z-line. The numbering, beginning from a reference Z-line, not only gives a meaningful number to each class, that is the charge Z of the particles that this class represents, but also eventually gathers lists (portions of lines) that were not grouped by the chaining procedure.

Section IV: Results and discussions

As explained, the (E,ΔE) image segmentation is aimed at replacing a manual Z-line extraction. The goal of the used procedure is to obtain lists of edge points characterized by their co-ordinates E and ΔE, each list containing points that belong to the same Z-line.

We have applied our contextual image segmentation system to different sorts of (E,ΔE) spectra: different projectile-target combinations, different energies and different rings of INDRA (i.e. different detection angles). Figures 10 to 12 show the obtained results.

The results representing the differentiation step are easy to illustrate as they correspond to the edge points localization in the image. It is more difficult to show what the chaining and numbering steps lead to. To do this, we will use another representation : the identification spectrum commonly used by physicists. It is obtained by transforming the (E,ΔE) representation to a (E,Z) representation as follows: for each particle in the spectrum, we calculate the distances d_1 and d_2 to the two nearest Z-lines Z_1 and Z_2 from each side. The new representation is obtained by replacing ΔE by the charge Z of the particle (a real number).

This corresponds to the following co-ordinates:

$$\text{The abscissa: } Z = Z_1 + \frac{d_1}{d_1 + d_2} = Z_2 - \frac{d_2}{d_1 + d_2}$$

$$(Z_2 > Z_1, \text{ generally } Z_2 = Z_1 + 1)$$

The ordinate: E

If the Z-lines are correctly extracted during the differentiation and chaining/numbering steps, this new representation will contain “straight lines” representing each a type of particles of

charge Z . The projection of such a representation on the Z axis shows the identification quality and precision.

In the various examples presented here, one can observe, even in noisy regions, the precision of the localization of the extracted Z -lines.

The directional filtering step (using a priori information), for image smoothing and S/N ratio enhancement gives interesting results as it leads to good differentiation performances. It is interesting to notice the S/N ratio enhancement effect: we can see in the Xe+Sn at 50 MeV case (figure 12) that Z -lines corresponding to noisy regions (high Z -lines) have been extracted correctly, as well as the extremities of most Z -lines.

During the differentiation step, the use of an optimal edge detector (in the sense of Canny's criteria) is of great help in obtaining a good optimisation of the edge points detection-localization trade-off as can be seen in the figures 11 and 12 that present a superposition of the original data and the obtained contours. This yields a precise particle identification as can be seen in the (Z,E) representations and their projections.

The a priori information used in this differentiation step were of great help in edge points extraction with detection-localization criteria optimization, even if the distances between Z -lines are known very approximately (the calibration is not known precisely: $\cong \pm 15\%$). Actually, the scale adaptation to local contour width is an interesting approach to avoid multiple responses to a single edge or edge position blurring that would occur if too thin or too broad differentiation operators were used.

The gaussian filter stability (LoG filter) in the scale space (that Poggio calls in [1] "a nice scaling property") is also an interesting property that avoids multiple responses to a single edge as the width of a Z -line is not precisely known.

Concerning the differentiation step, one can notice, that even if its direction is not orthogonal to the contours, the edge localization is still precise. We had planned to modify the direction of differentiation, so as to make it orthogonal to the contours, using the a priori information available, but as can be seen in the various examples presented here, this was not necessary.

In figure 10, an undesired class of events resulting from an abnormal behaviour of the detector and not from a physics mechanism under study has appeared (horizontal line). It is interesting to notice that it has been completely ignored in the differentiation step. The directional smoothing step and the differentiation operator's scale adaptation to the lines widths is at the origin of this result. This kind of undesired classes can be eliminated in this way, as soon as their statistics are low enough compared to the Z -lines statistics.

Figure 11 is an example of $(E,\Delta E)$ spectrum where a large number of Z -lines correspond to low statistics, particularly the highest lines. One can see that our method extracted nearly all the Z -lines that human vision can distinguish.

Figure 12 presents a case where a large number of classes are to be extracted (up to $Z=54$). This example shows the necessity of operators scale adaptation during the smoothing and

differentiation procedures. Here again one can notice the high performances that are obtained in cases of poor statistics.

We can then say that the goals of the edge detection procedure were fully accomplished:

- Only one response to a single (even noisy) edge.
- A good localization of lines centers.

It's coupling to the preliminary directional filtering, and the use of a LoG filter whose scale was adapted to local characteristics in accordance with a priori information available, yields high quality performances.

Concerning the chaining step, the nature of our application and the good results that preceding steps yield to, justifies the use of very simple chaining rules, which are constrained by a priori information. The numbering step yields correct Z-lines extraction.

In an actual particle identification scheme, the extracted and numbered Z-lines can be fitted by "appropriate" functions (appendix 1) so that all detected particles on the spectra (even cut off ones) are identified as physically significant extrapolation to very low statistics region can be achieved.

Some rare cases may need the use of extra rules. Some atypical $(E, \Delta E)$ spectra may actually contain perturbations consecutive to abnormal behaviours of the experimental device. Such an example is presented in figure 13. We did not focus on such cases as they concern very few spectra. Some anomalies (slit scattering) may have "physical" solutions and may be easily eliminated by a selection based on particles multiplicity criteria. This leads to a "cleaned" $(E, \Delta E)$ spectrum that can then be processed as described in this paper.

However one can see that even in these particularly noisy cases, satisfactory results are obtained in terms of edge points extraction (especially in figure 13 a and b). This shows the significant help that a priori information offer during the directional smoothing and the differentiation operator's scale adjustment.

Section V: Summary and conclusion

We have presented a contextual image segmentation system that is designed to process physical spectra in order to extract automatically roof edge contours in noisy cases. This image segmentation approach was chosen to solve an unsupervised data classification problem in cases where more usual data classification methods do not lead to the desired optimal partitioning. The approach we suggest is based on the fusion of two types of information in the segmentation process: experimental data and a priori information. This merging is responsible for the good differentiation quality, especially in noisy cases.

A first regularization of the differentiation is achieved by mean of a presmoothing step. Directional smoothing using a priori information yields a significant S/N ratio improvement. These a

priori information are also taken into account during the differentiation step, where an optimal roof edge detector (in the sense of Canny's criteria) is used. Its scale is dynamically adapted to the local characteristics of the image. The very satisfactory results that these operations lead to simplifies significantly the chaining and numbering steps. Different results obtained by our contextual picture segmentation system have been presented. They show that it brought a satisfactory solution to our automatic data classification problem.

Such an approach can certainly be used in other fields of 2D data or pictures segmentation, where a priori information can provide an approximate description of contours characteristics. It certainly results in better performances than using a general (i.e. non contextual) picture segmentation system . This is particularly true in various fields of physics, where underlying (even not well known) processes offer the possibility of extracting such information.

Acknowledgements:

We are grateful to the INDRA collaboration staff whose invaluable support made this work possible. We particularly wish to thank Dr J.C Steckmeyer from LPC (Caen) for helpful discussions and comments.

References:

- [1]: V. Torre, T. A. Poggio. IEEE transactions on Pattern Analysis and Machine Intelligence, vol. PAMI-8, n° 2, MAR 1986, pp 147-163.
- [2]: J. Canny. IEEE transactions on Pattern Analysis and Machine Intelligence, vol. PAMI-8, n° 6, NOV 1986, pp 679-698.
- [3]: A.N. Tikhonov. Soviet math. Dokl., vol 4, pp 1624-1627, 1963.
- [4]: A. Witkin. Proc. IJCAI, Karlsruhe, Germany, 1983, pp 1019-1021.
- [5]: A.L. Yuille, T. Poggio. Massachusetts Inst. Technol., Cambridge, A.I Memo 722, 1983.
- [6]: A.L. Yuille, T. Poggio. Massachusetts Inst. Technol., Cambridge, A.I Memo 730, 1983.
- [7]: D. C. Marr, E. C. Hildreth. Soc. London B, vol. 207, 1980, pp 187-217.
- [8]: D. Marr, T. Poggio. Proc. Roy. Soc. London B, vol. 204, 1979, pp 301-328.
- [9]: E. Plagnol & al. Nouvelles du Ganil n° 44, Fév 1993.
- [10]: J. Pouthas and al. To be submitted to NIM.
- [11]: W. L. G. Koontz, K. Fukunaga. IEEE trans. on Computers, vol c-21, Feb 1972, pp 171-178.
- [12]: E. Diday. Revue de statistique appliquée, vol XIX n°2, 1971, pp 19-33.
- [13]: A.Benkirane. Université de Caen, Thèse 1994.
- [14]: P. Lutz. Nuclear Physics A545, 1992, pp 419-432.
- [15]: H. A. Bethe. Ann. Physik 5, 1930, pp 325.
- [16]: J.F. Ziegler, J.P. Biersack, V. Littmark. Vol. 1, Pergamon Press, 1985, ed. by J.F. Ziegler.
- [17]: F.Hubert. Ann. of Phys, 1980, n°5, pp 1-214.
- [18]: L.C. Northcliffe, R.F. Schilling. Cyclotron Institute, Texas A&M University.
- [19]: C.J.W. Twenhöfel & al. NIM, vol B51, 1990, pp 58-62.
- [20]: V. Nalwa, T. Binford. IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. PAMI-8, n° 6, SEP 86, pp 699-714.
- [21]: J. Canny. Massachusetts Inst. Technol., Cambridge, tech. Report 720, 1983.
- [22]: L.Spacek. Ph. D dissertation. Essex University, colchester 1984.
- [23]: E.C. Hildreth. Massachussets Institut of technologie, Cambridge, A.I. memo 579, 1980.
- [24]: A. Huertas, G. Medioni. IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. PAMI-8, n° 5, SEP 86, pp 651-664.
- [25]: J. C. Steckmeyer. Nouvelle du Ganil n°40, Juillet 1991.

Appendix 1:

The aim of fitting all the Z-lines that have been automatically extracted by a unique analytical expression whose parameters depend on Z is to have a function that can be extrapolated to higher energy domains. In this way if N Z-lines have been extracted, Some other higher Z-lines (N+1, N+2,...) can be obtained with enough precision using the performed fit if an appropriate function expression is used. This permits then the identification of all cut off points in (E,ΔE) spectra that belong to regions where no Z-lines are perceptible (and then not extractable automatically) because of lake of statistics (figure 11 for example).

We use for this fit a function whose expression has been defined experimentally so as to reproduce well Z-lines behaviour for all the energy domain in the (E,ΔE) spectra. We used in our application:

$$f_Z(E) = a_1(Z) + \frac{a_2(Z)}{E + a_3(Z)} + \frac{a_4(Z)}{E^2 + a_5(Z)}$$

$f_Z(E)$ is a set of functions of E whose parameters are polynomials of Z.

$$a_j(Z) = \sum_{i=0}^3 \alpha_{ji} Z^i \quad \text{for } j = 1, 2, 3.$$

$$a_j(Z) = \sum_{i=0}^4 \alpha_{ji} Z^i \quad \text{for } j = 4, 5.$$

This expression furnishes a Z-lines compact representation (instead of keeping all the Z-lines points co-ordinates). Indeed a few number of parameters (generally about 20) represent the whole set of Z-lines of a given spectrum.

The unsupervised picture segmentation method described in this paper furnishes a set of lists representing each a Z-line and containing edge points co-ordinates that are used for the fit procedure. This fit yields a parameterized expression $f_Z(E)$ whose parameters depend on Z. It permits the generation of a grid of Z-lines that reproduces well the automatically extracted Z-lines as well as some Z-lines corresponding to too few statistics (which are not extractable automatically).

The so obtained expression is used for the identification procedure by affecting each of the particles on the spectra to the nearest corresponding Z-line, as described in chapter IV.

Ideally, finding a mathematical expression $f_Z(E)$ that can yield to a simple resolution of the equation:

$$\Delta E - f_Z(E) = 0$$

would have been more efficient practically, as each particle characterized by its co-ordinates E and ΔE would be identified by calculating the number Z that resolves the equation here above.

This was not till now possible as we could not find an expression that not only fits precisely (E,ΔE) spectra Z-lines, but corresponds to a simple resolution of this equation as well.

An example of obtained grid is presented in figure A.1.

Figures captions

☛ **Figure 1: Different representations of the INDRA detector.**

The top view shows a cut along the beam axis.

The middle view shows a schematic 3D representation of the different rings.

The bottom view shows a computer representation of the detector in an open configuration.

☛ **Figure 2: The INDRA detector cell and the associated 2D histograms.**

Depending on the association of layers, identification of different products is achieved

☛ **Figure 3: Some examples of $(E, \Delta E)$ spectra corresponding to rings 1 and 2 of INDRA..**

This figure shows different sorts of spectra and the difficulties that the automatic data classification problem implies: the Z-lines location varies significantly, a large number of Z-lines are with low statistics...

☛ **Figure 4: Some examples of Z-lines slopes and inter-distances used as a priori information.**

☛ **Figure 5 : convolution mask characteristics are adapted to local context.**

Z-lines inter-distances are in MeV unit (a priori information). they are converted to pixel (channel) unit using the calibration values (leading, for example, to the parameter 'a' estimation in pixels).

☛ **Figure 6: A directional smoothing result example using a priori information.**

This smoothing is a first regularization of the differentiation.

It also leads to an improvement of the S/N ratio.

☛ **Figure 7: LoG filter width importance in noisy edge case.**

This figure justifies the obtention of a multi-response to a single edge, when the scale of the LoG filter is too small compared to the edge scale, as in figure 9.a.

☛ **Figure 8: Result of our differentiation approach on smoothed spectrum of figure 6.**

The differentiation is achieved by convolving each column (1 pixel thin) of the smoothed image by a LoG filter whose scale is adapted to the edge width locally.

☛ **Figure 9: Obtained edge points when no a priori information are used.**

The smoothing step is achieved here using a gaussian symmetric filter with (a) $\sigma = 2$ pixels and (b) $\sigma = 6$ pixels .

In the differentiation step, the LoG filter's scale is constant: (a) $\sigma = 2$ pixels and (b) $\sigma = 6$ pixels

☛ **Figure 10: First example of Z-lines extraction.**

The horizontal line in the $(E, \Delta E)$ spectrum results from an abnormal behaviour of the detection device (slit scattering).

It has been completely ignored by our contextual segmentation system.

☛ **Figure 11: Second example of Z-lines extraction: A case of large number of Z-lines with low statistics.**

Nearly all the Z-lines that are visible by eye have been extracted correctly.

☛ *Figure 12: third example of Z-lines extraction: A case of large number of classes.*

*Very noisy Z-lines (around $Z=48$) have been processed correctly.
Precise identification of particles is obtained up to $Z=54$, as can be seen on
the identification spectrum and its projection.*

☛ *Figure 13: Some particular cases are difficult to process simply by a segmentation procedure
(resolution decrease, lake of statistics, slit scattering...)*

☛ *Figure A1: An example of generated grid, obtained by fitting extracted Z-lines.*

Figure 1

Figure 2

Figure 3

Figure 4

Figure 5

Figure 6

Figure 7

Figure 8

Figure 9

Figure 10

Figure 11

Figure 12

Figure 13

Figure A1