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# PATTERN CLUSTERING AND MAPPING METHODS FOR PRESENTATION OF NUCLEAR REACTOR NOISES*

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Кластеризация и визуализация образов
как метод представления реакторных шумов

Рассмотрены вопросы использования кластерного анализа и визуализации для изучения структуры многомерных данных. Основная цель работы состоит в том, чтобы показать потенциальные возможности и отрицательные стороны детерминистских методов распознавания образов, таких как кластеризация и визуализация, а также отметить роль алгоритмов поиска глобального экстремума, используемых для анализа многомерных данных. Показано, что в применении к шумовой диагностике ядерных реакторов методы распознавания образов, дополненные методами анализа их структуры, могут существенно повысить эффективность диагностирования и сократить исходный объем анализируемой информации. В качестве примера приведен анализ шумовых состояний реактора ИБР-2.

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Dzwinel W., Pepyolyshev Yu. E10-94-61

Pattern Clustering and Mapping Methods for Presentation
of Nuclear Reactor Noises

Some problems of using cluster analysis and visualization to study multidimensional data structure are discussed. The main point of the work is to demonstrate potentialities and drawbacks of deterministic methods for pattern recognition, such as clustering and visualization, and to note the role of global extremum search algorithms used in various multidimensional data analysis methods. The methods of pattern recognition together with the methods of pattern structure analysis applied to noise diagnostics of nuclear reactors are shown to be able to essentially increase the efficiency of diagnosis and to reduce the scope of the analyzed information. The analysis of the noise conditions of the IBR-2 reactor is given as an example.

The investigation has been performed at the Frank Laboratory of Neutron Physics, JINR.

Communication of the Joint Institute for Nuclear Research. Dubna, 1994

# 1. INTRODUCTION

Many modern diagnostics and control systems as for example the nuclear reactor safety systems, suffer from the fundamental disadvantage (see [1,2,3]).

**They give large amount of abundant information that cannot be used as efficiently as required.**

The pattern recognition approach for the nuclear reactor noise analysis with pattern mapping methods proposed by the authors could be an issue to overcome this trouble.

The main goal of this lecture is to show the potential possibilities and drawbacks of deterministic pattern recognition methods as:

- **clustering,**
- **mapping of patterns,**

and the role the global optimization algorithms:

- **simulated annealing SA,**
- **threshold accepting TA,**

play for presentation and analysis of multidimensional data. The definition of multidimensionality assumed involves the recorded data to be represented as points in the Banach space.

The examples presented concern the IBR-2 Dubna (Russia) nuclear reactor data. They were collected during the time period 1988-1992.

**Some results and conclusions presented here have preliminary character because a lot of fundamental questions are still open, are in project stage or are under realization.**

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## 2. INTEGRALS AND DIFFERENTIAL CHARACTERISTICS

The simplest monitoring of a nuclear reactor consists in tracing whether some pre-determined parameters overcome some pre-determined level. **Fig.1a** can serve as an example, where the integral parameter - power fluctuations ε of the pulsed research nuclear reactor IBR-2 - during two year operation period is depicted. However, because of significant ε oscillation and the closeness of the reactor stop threshold (≅10%) the threshold criterion is insufficient anymore. A more accurate criterion is necessary to monitor early failures, degradation trends and their possible sources to determine as precisely as possible the necessity and the time of restoration. The restoration action undertaken in the proper time could increase, in turn, the reactor life time.

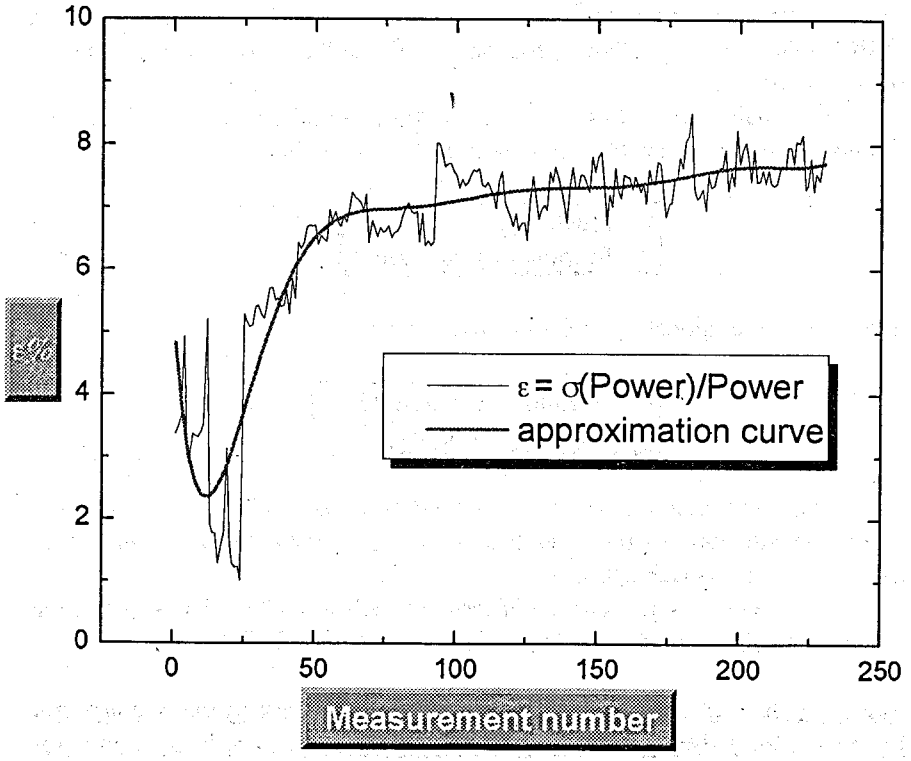


**Fig.1 a.** The power fluctuations ε during the IBR-2 reactor operation period from the end of 1987 to the beginning of 1992. The approximated degradation is shown



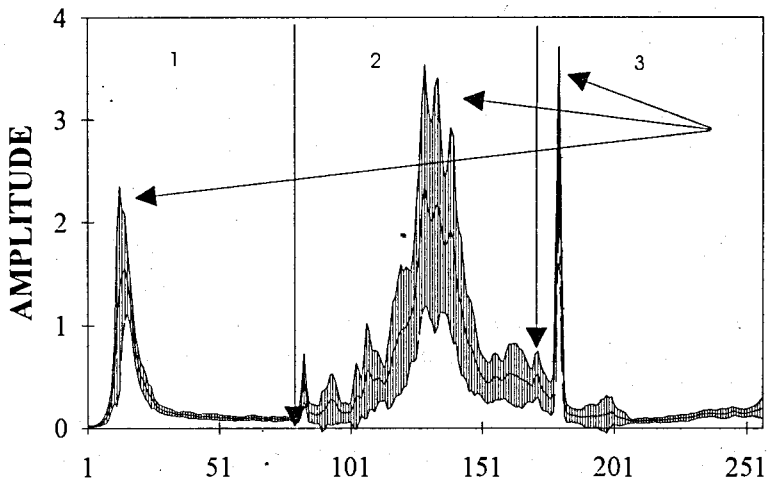


**Fig.1 b.** The average power spectral density (PSD) (from almost 200 spectra covering the IBR-2 reactor two years operation period) with ±σ in each of frequency channels.

The analysis of such a picture may consist in, e.g.:

- splitting the frequency interval into three regions reflecting main sources of power fluctuations and analysing them separately,
- the main peaks extracting and analysis

The differential characteristics like time series or, above all, power spectral densities (PSD) and vibration spectral densities of the controlled mechanical parts of construction (e.g. moving reflectors, pumps, cooling system components), are more sensitive to the reactor operation changes. The changes in, e.g., PSD form (may not be followed by the changes of their respective integrals) can reflect an abnormal reactor operation, incipient degradation, and even help to find the source of failures. Nevertheless, in contrast to the clear threshold criterion for integrals, the spectra and other differential characteristics must be conditioned in a quite different way. The criteria can be built on the basis of

- **extraction, evaluation and analysis of characteristic details of the spectral densities, e.g., peaks analysis, domain split, *etc.* (see Fig.1b),**
- **discriminants approach,**
- **pattern recognition and neural network.**

The first item refers to the most popular, especially in experimental physics, and very important method of spectrum's analysis. This method gives good results for relatively low number of data, of stable and static character. The results of such an analysis (the peaks areas, positions, lengths of the highest or lowest gradients, *etc.*) can be also used for the further approaches itemized above.

## 3. PATTERN RECOGNITION - DATA CLASSIFIERS

Let us consider the pattern recognition approach which, in our opinion, should fill the gap between the standard "passive" monitoring system and, in the future, an intelligent supervisor.

Pattern recognition is the very wide branch of science covering **deterministic** (digital) and **syntactic** (logical) methods of patterns classification, recognition, processing and analysis. It encompasses such widely known problems as image processing, features selection, data classification - clustering, discriminants analysis, principal component analysis, *etc.*

### 3.1 Discriminants

The method of discriminants [4] consists in comparison of a subsequent spectrum with the specified number of stencil patterns or a base (possibly the bases) of a number of spectra corresponding to the known system responses. The set of discriminating parameters has to be defined in such a way that they describe different features of the signal representation. Membership of an incoming spectrum to the base (or its distance to the stencil pattern) determines immediately the sort of information carried by the current signal. Let us suppose, however, that the incoming spectrum distortion represents unessential deviation from the normal operation of a nuclear reactor. The new spectrum must not be neglected but has to be included as the nearest base member. The degradation processes like ageing, requiring the continuous base update, contribute to its expansion and compactness loss. The new discriminants have to be introduced to prevent the membership mistakes and an accuracy loss. Additionally, to establish the relationship of tens of processes controlled the exponential increase of computational power can be anticipated. Therefore, the authors recommend to use this method for monitoring of independent reactor components with well defined and stable signal representations, covering rather short time scales.



### 3.2 Clustering

Just the clustering was the first of pattern recognition methods (to the best of authors' knowledge) applied for a reactor data monitoring by Gonzalez R.C. et al. (1974) [4]. **Fig.2** presents the main idea of this approach. The mapping of patterns application constitutes one of many improvements made by the authors of this paper to this idea.

The noise patterns, as for example the power spectral densities, recorded subsequently during reactor operation and represented as points in the N-dimensional Euclidean space are classified using clustering procedures. Changes of the clusters structure, as for example the new clusters appearance, can reflect an anomalous reactor operation. The authors accomplished diagnostic system which bases on this idea (it differs considerably from the prototype quoted, see authors' earlier works).

**Figs.3a,b** show how the clustering part of this system works. The analysis of figures shows which one of moving reflectors is responsible for PSDs distortion. The question arises:

**How can an operator analyse the mutual relationships of maps, as those presented above, for multicomponent (not only three) noise patterns?**

The maps contain too many details, but time diagrams like that in **Fig.3b**, in turn, says nothing about the cluster structure. Moreover, some distinct changes in the OPO vibrations spectra with distinct responses in PSD pattern do not create separate clusters.

For long term nuclear reactor diagnostics point of view the processes like ageing must be taken into account. They may influence the clusters structure in a quite different way . To control such effects, detailed analysis of the full recorded clusters structure is necessary. Therefore, apart from the point-to-cluster membership, additional information as: cluster compactness, cluster-to-cluster distances, results of statistical analysis, *etc.*, must be supplied to an operator. Finally, the advantage of information squeezing obtained by the clustering techniques may be seeming only. Additionally, the numerical analysis is not able to give any information about the clusters shapes, which is very important especially when the clusters forms are non-spherical in the chosen space and undergo the continuous changes.

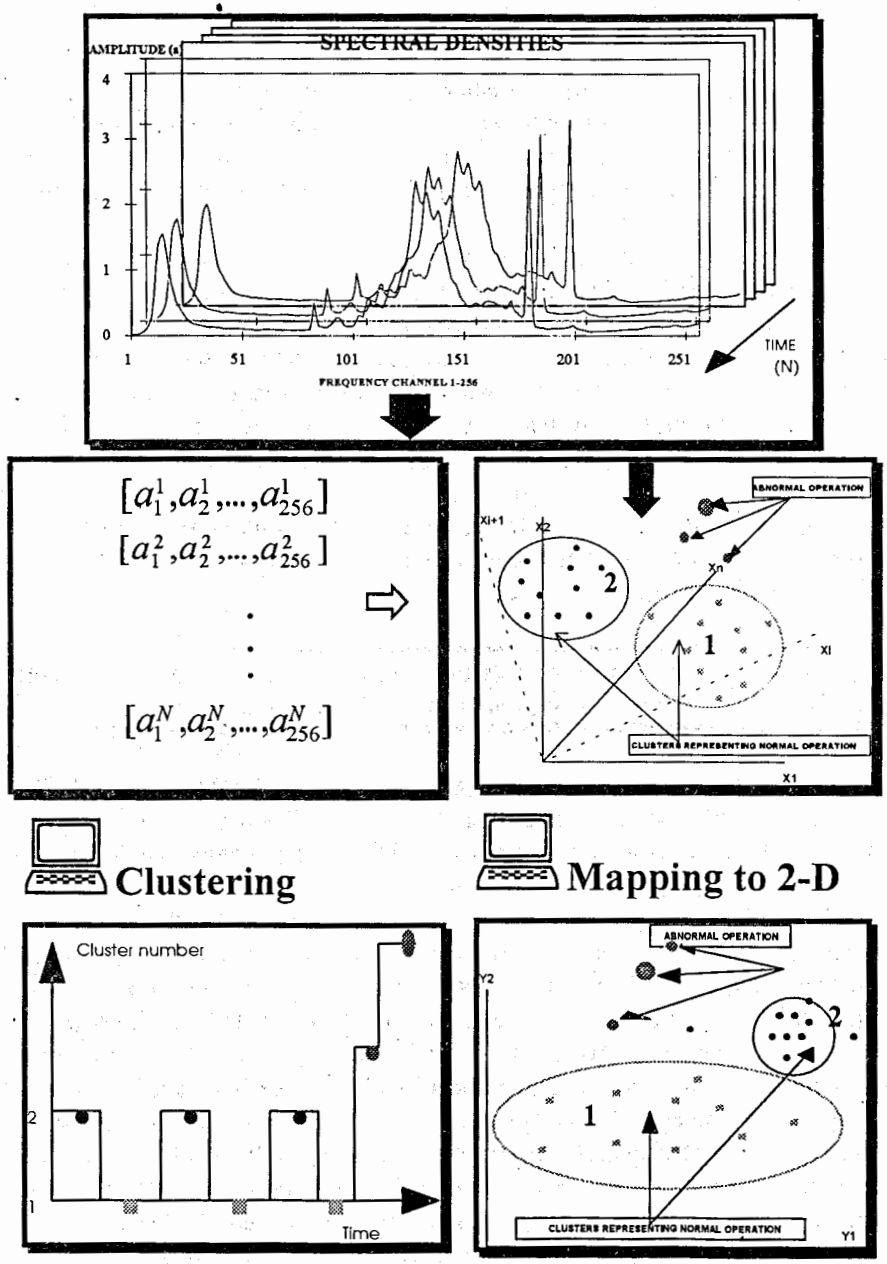


**Fig.2** The conception of clustering and mapping application for spectral data classification and analysis



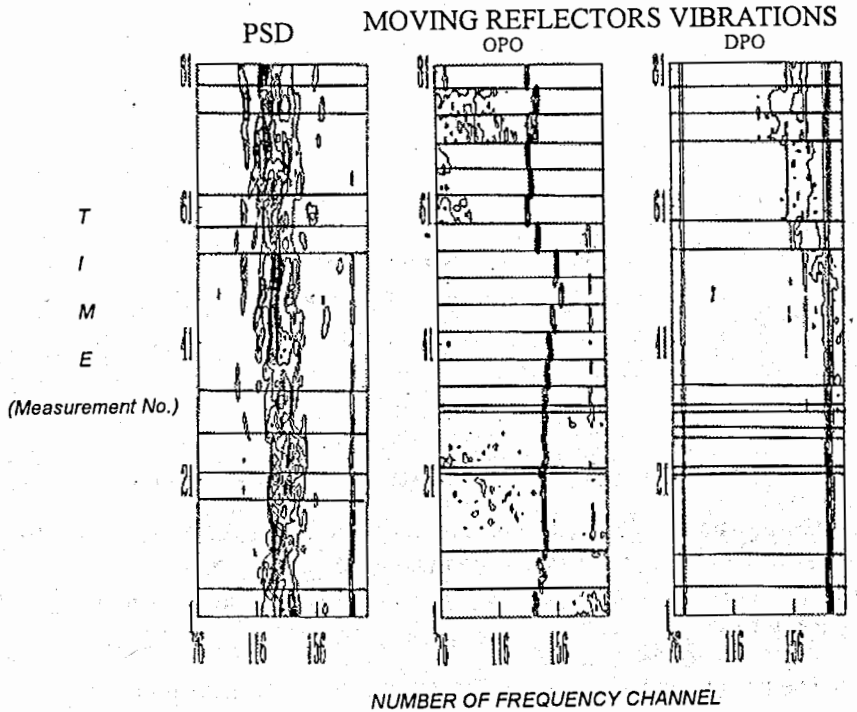


**Fig.3a.** Topological maps of the PSD and spectral densities of the moving reflectors vibrations (the main -OPO - and additional one - DPO) for the IBR-2 (Dubna) reactor two years' operation period. The lines drawn correspond to the cluster-to-cluster transitions presented in Fig.3b

Just these sorts of clusters are responsible for the ambiguous clustering results presented in **Fig.4**. Six different clustering algorithms were used for the reactor data [5], and six different results were obtained (however one can see that some stable clusters are present in all or almost all diagrams shown). The sources of differences between **K-mean** type algorithms and **Moving** ones are obvious. These two methods base on different aggregation principles each of them uses. The substantial differences inside these groups are caused by the fact that each result represents the other local minimum of a functional ("energy") minimized in course of clustering. The example presented in **Fig.5** explains better this problem. But the ways to find the global minimum will be discussed at the end of this paper.

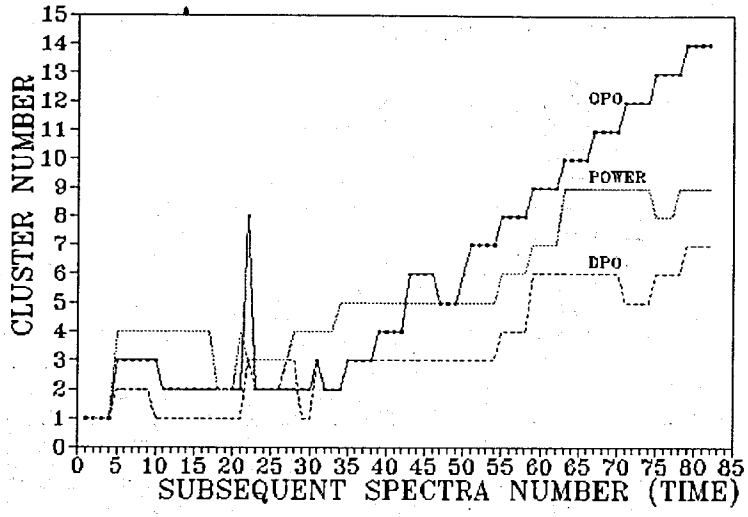


**Fig.3b.** The point-to-cluster membership diagram for the PSDs and spectral densities of the moving reflectors OPO/DPO vibrations. The diagram shows to which cluster (represented by numbers 1-14) the subsequent reactor spectral density falls

The trouble with clustering is not the only one. The next problem is the proper selection of space where N-dimensional points (spectra representations) are classified. **Fig.6** shows the clustering results of the three skew lines in the six five-dimensional spaces determined by the metrics chosen [5]. This time, the hierarchical clustering algorithms were used.

More troubles arise for the very high dimensions, M>100 (see [6]). Strange effects (seemingly out of imagination) appear, as is presented in **Fig.7a.** It represents the two-dimensional pattern (result of mapping) of the 100-dimensional pseudo-random points uniformly distributed in the hypercube **C(1, 0)**. The points marked are space averages of the total 1000 points generated. This result comes from the fact that for N-dimensional space the probability that the randomly generated point gets closer to the hypercube centre decreases as $R^{N-1}$ while for the reverse direction the probability is determined by the box size. These results mean that in N-dimensional space the points "infected" by random noise create quasi-hyperspheres. The random component change (e.g. noise increase) may be the reason of the two clusters emergences, as is shown in **Fig.7b**. **Fig.5** shows, however, that the standard clustering methods need five clusters to reveal this structure, instead of two. Decrease of the number of clusters causes the internal sphere sticks to the other, one out of external clusters (see Moving 1 algorithm in **Fig.5)**.



Direct use of the extraordinary human ability for pattern recognition seems to be the best way for instant clusters structure analysis. To resolve this problem two main questions arise, the conceptual and technical ones, i.e.:

- **How can one compress the multidimensional picture into the two- (or three-) dimensional one, preserving the real cluster structure?**
- **How can one visualize the best resulting pictures for analysis?**

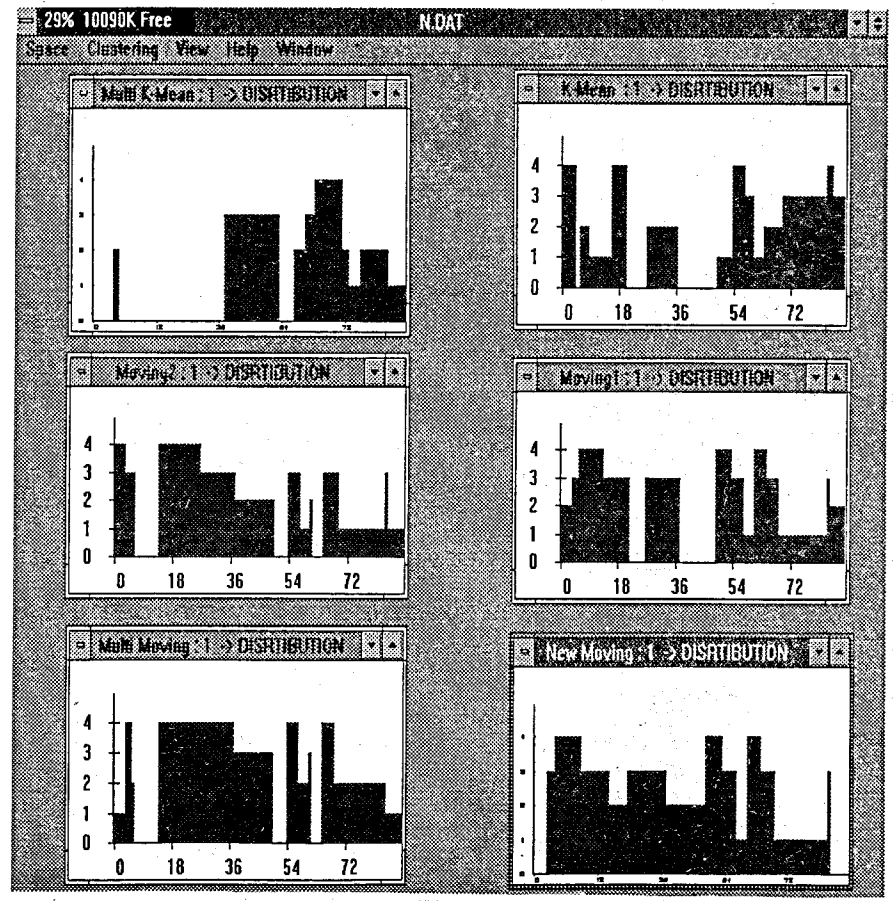


**Fig.4.** The results of six algorithms applied for the IBR-2 reactor data (PSD) clustering. The "energies" reached - the average standard deviations in clusters - for each method are as follows (from the left upper corner in rows): 1450, 1490, 1490, 1512, 1474, 1434. The closest to the global minimum is the *New Moving* algorithm.

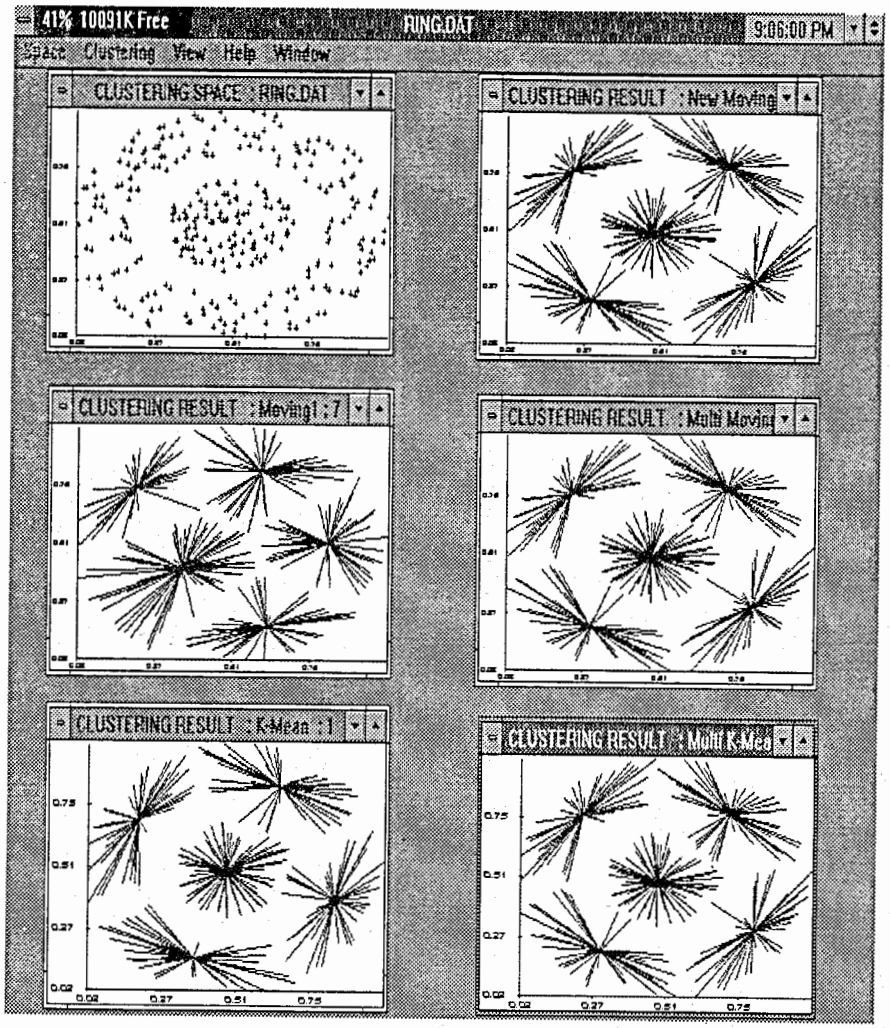


**Fig. 5.** The results of clustering of the clusters structure shown in the first chart using five non-hierarchical methods. Minimum five clusters are necessary to represent this structure adequately. The lesser number of clusters assumed will cause clumping the internal cluster with an outer one (like for a method Moving 1). One can see that any of methods gives 100% internal sphere selection. Some of its points belong to the outer sphere clusters



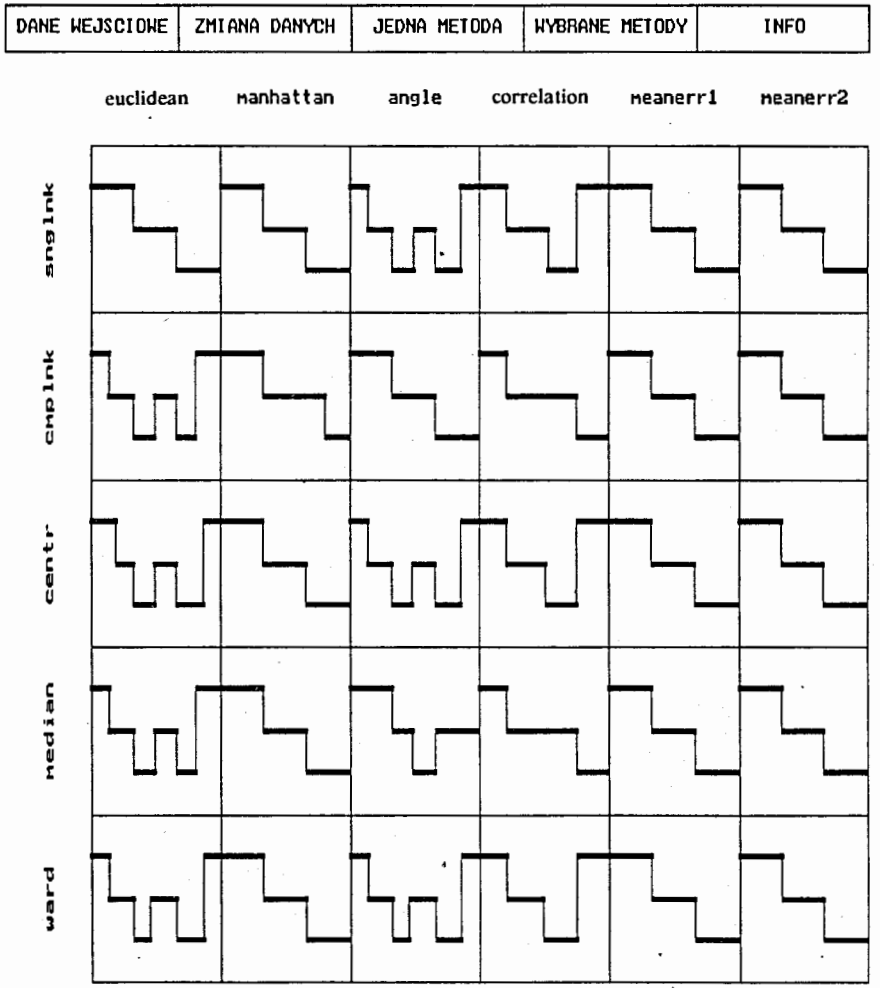


**Fig.6.** The clustering results for the structure which consists of three non-crossing lines in the 5D space. Five hierarchical algorithms (sngInk, cmpInk, centr, median, ward) were used for the six different metrics (euclidean, manhattan, angle, correlation, meanerr1, meanerr2). Only a few combinations of algorithm-metrics detect the structure adequately, i.e., three separate clusters represented as three equal stairs on the diagrams shown

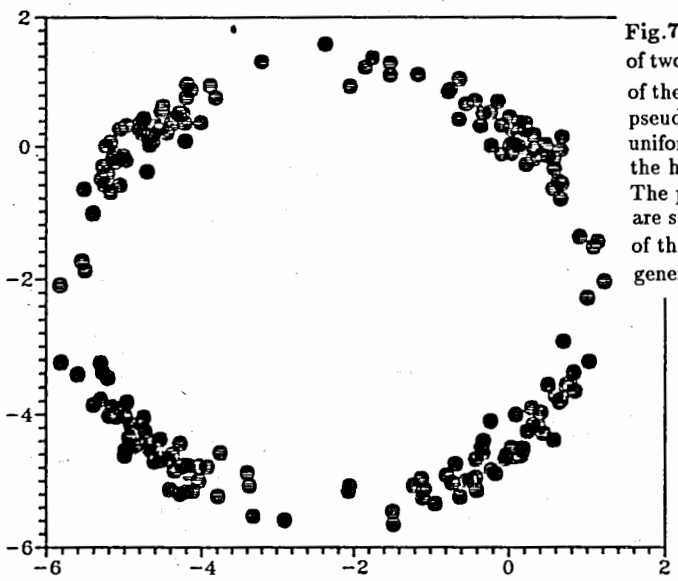

Fig.7a.The example of two-dimensional mapping of the 100-dimensional pseudo-random points uniformly distributed inside the hyper cube $\mathbf{c(1,0)}$. The points marked are space averages of the total 1000 points generated

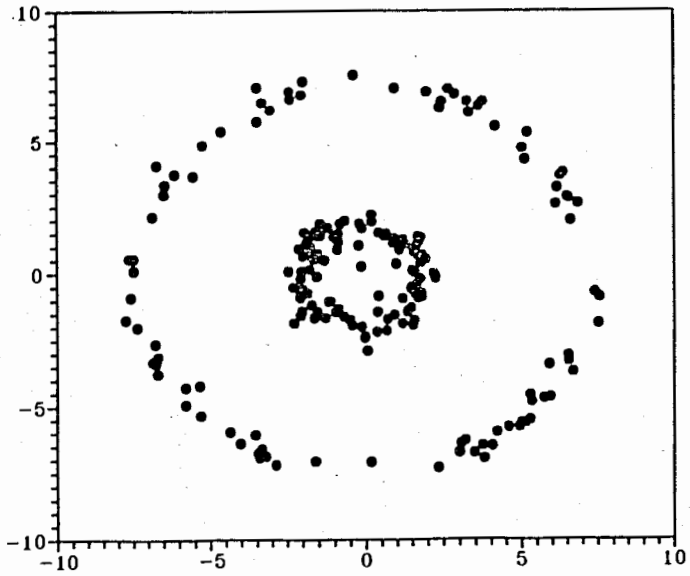

Fig.7b.Effect of two quasi-hyperspheres appearing with a random component change. The result of mapping of the 100-dimensional points into 2-D space. The points were randomly generated in hypercubes $\mathbf{c(2,0)}$ and $\mathbf{c(0.5,0)}$ respectively. The points marked are space averages of the total 1000 points generated



Up to now, to the best of authors' knowledge, the mapping of patterns techniques are the only way to resolve the first problem.

## 4. PATTERN RECOGNITION - MAPPING OF PATTERNS

Generally, the mapping of patterns algorithm realizes the transformation $\Re$;

$$\Re; R^N \supset \omega \xrightarrow{\Re} \omega' \subset R^n, N >> n, E(\omega, \omega') = \min$$

where, *E(.)* - the functional, often called "energy", which differentiates the sorts of algorithm used. **Fig.2** shows the role the mapping can play.

There are two sorts of mapping algorithms:

- **linear mapping:**

*a.* ***simple projection***
*b.* ***principal component mappings***
*c.* ***declustering mapping***
*d.* ***projection pursuit***
*e.* ***least squares mapping***

- **non-linear mapping:**

*a.* ***multidimensional scaling***
*b.* ***triangulation mapping***
*c.* ***k-nearest neighbour mapping***

A good overview of mapping techniques is presented by W.Siedlecki et al. (*Pattern Recognition*, **21**(5), 1988) [7] and M.Aladjem (*Pattern Recognition*, **24**(6), 1991).

For visualization of the real multidimensional complex structures (e.g. non-spherical, elongated, oblate or patterns like that presented in **Fig.5**), as was shown by the authors in the earlier publications [8,9,10], the non-linear

methods are recommended. Especially those, which use Sammon's criterion (the receipt of "energy" computation).

## *Sammon's Criterion*

**let**

$$\omega=\left\{\mathbf{x}_j;\mathbf{x}_j=\left(x_j^1,x_j^2,\ldots,x_j^N\right),j=1,\ldots,M\right\}$$

$$\omega'=\left\{\mathbf{y}_j;\mathbf{y}_j=\left(y_j^1,y_j^2,\ldots,y_j^n\right),j=1,\ldots,M\right\}$$

**then**

$$E(\omega,\omega')=\sum_{j<i} s_{i,j}^{w\cdot m}\cdot(s_{i,j}-s'_{i,j})^{m}=\min$$

**where**

$$s_{i,j}=\left(\mathbf{x}_i-\mathbf{x}_j\right)\circ\left(\mathbf{x}_i-\mathbf{x}_j\right)$$

$$s'_{i,j}=\left(\mathbf{y}_i-\mathbf{y}_j\right)\circ\left(\mathbf{y}_i-\mathbf{y}_j\right)$$

and both $w$ (equal to 1,0 or -1) and $m$ (mostly equal to 2) are problem dependent parameters. Let us assume that the clusters are not spherical and they may reflect some operation trends (e.g. the nuclear reactor ageing), which may cause clusters elongation. Substituting $w$=1 and $m$>3, the oblate clusters are stretched out additionally, which may cause overlaps in ω', while for $w$ = -1 the trend of better preservation of the nearest neighbours distances is observed with simultaneous deterioration of the long range structure.

In that case consider that $w$=0 and $m$=2. Then:



***the method consists in preservation of the Euclidean distances between M points of N-dimensional space in the n-dimensional one, where n<<N.***

The problem arises:

**How to find the global minimum of E(), to fulfil the mapping criterion?**

Each of the mapping algorithms based on the Sammon criterion as for example the Niemann method [11], tries to find the minimum of **E()** using sophisticated but still standard techniques. It means that the results obtained for relatively high dimensions and different starting configuration (first iteration) are, as a rule, different. They represent miscellaneous local minima of **E(.)** being the **first kind** of artifacts produced by the mapping. The resulting two-dimensional pictures may show the points of different clusters partially (**Fig.8a**) mixed. It might happen by chance, of course, that the better minimum will be obtained.

To gain a minimum closer to the global one, the **Simulated Annealing (SA)** model can be used (Kirkpatrick, S. et al. [12]). The sketch below presents the most elegant (and efficient) mutation of **SA** model, i.e., **Threshold Accepting** algorithm, presented first by Dueck, G. and Scheuer, T. [13]. The classical methods trace the configuration space along a path with decreasing step-by-step "energy", which causes the algorithm stop in the first encountered local minimum. The **TA** (and **SA**) algorithm allows one to free from the local minimum and inspect the wider area in search for the global solution. The uncertainty factor T decreasing gradually in accordance with the chosen annealing paradigm $f(T,t)$ to the zero value, represents the "temperature" of the algorithm. At the end, to obtain the higher accuracy (to gain the "bottom" of the minimum reached), a classical minimization method may be used. As shown in **Fig.8b,** much better result was obtained. The various clusters do not overlap each other. However, the considerable increase of computational load with simultaneous decrease in efficiency are the main drawbacks of this approach.

## *Threshold Accepting*
### *General Purpose Optimization Algorithm*

| | |
|---|---|
| $t=0,\ E_t=E(\omega,\omega_t'),\ T=T_0$ | • Set the initial configuration |
| **AA**: $t = t + 1$ | **Main iterations loop** |
| $l = rnd\ (1,...,M)$<br>*for* i=1 *to* n<br>$\beta = rnd\ (-1,...,1)$<br>$y_l^{t+1} = y_l^t + \beta \cdot Rstep(T)$<br>*endfor* | • Choose a random point<br>• and move it at random |
| $E_{t+1}=E(\omega,\omega_{t+1}')$<br>$\Delta E = E_{t+1}-E_t$ | • Compute energy for new configuration and energy change |
| *if* ($\Delta E$ stable) $T = f(T,t)$ | • Use annealing model $f()$ to decrease the temperature T |
| *if* ($\Delta E < T$) *goto* **AA** | • Accept new configuration |
| *else* | |
| *for* i=1 *to* n<br>$y_l^{t+1} = y_l^t$<br>$t = t - 1$<br>*endfor* | • Reject new configuration |
| *endif* | |
| *goto* **AA** | **Go to the beginning** |



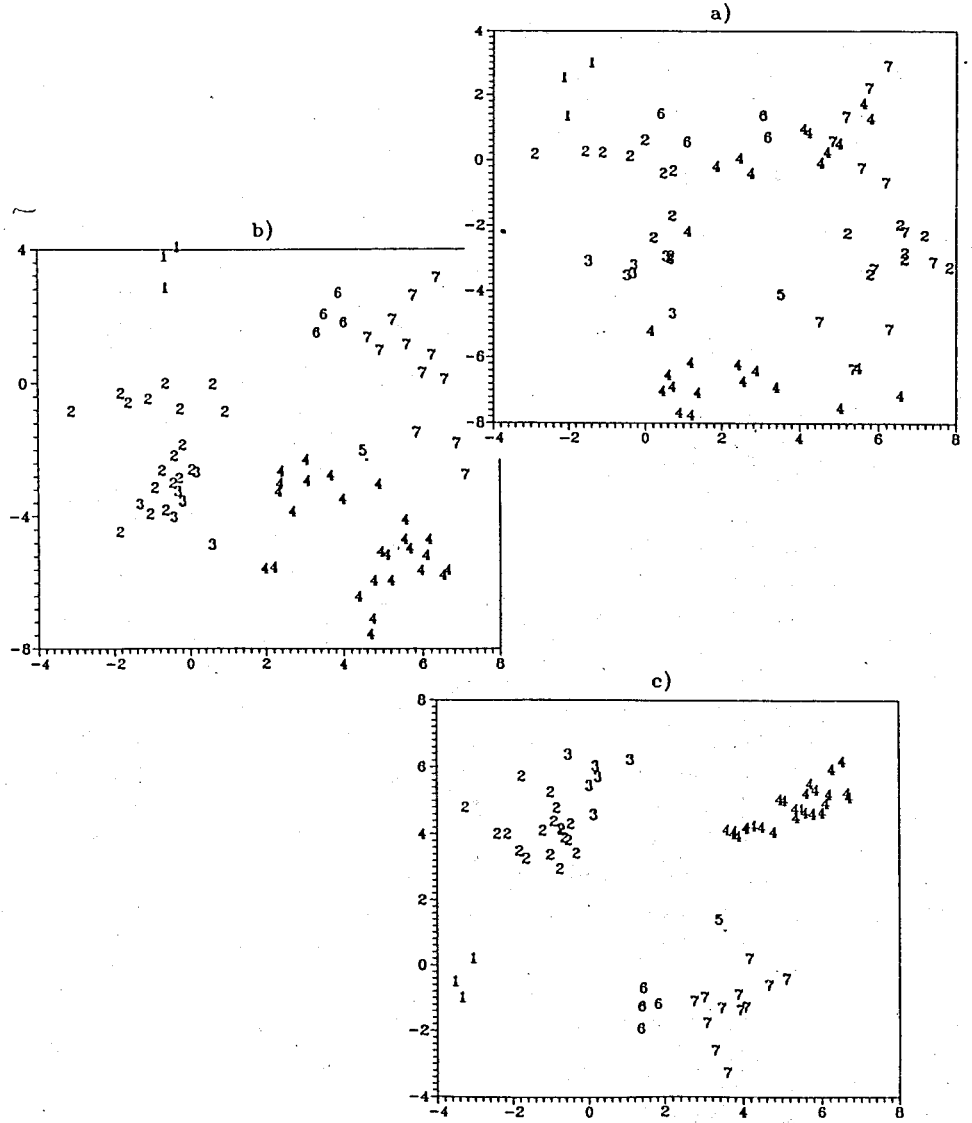


**Fig.8** The results of mapping of the pulsed nuclear reactor IBR–2 data (256-dimensional) into 2–D space for three mapping algorithms used :
a) the old Niemann method,
b) simulated annealing approach,
c) Niemann's algorithm with pre–clustering of data

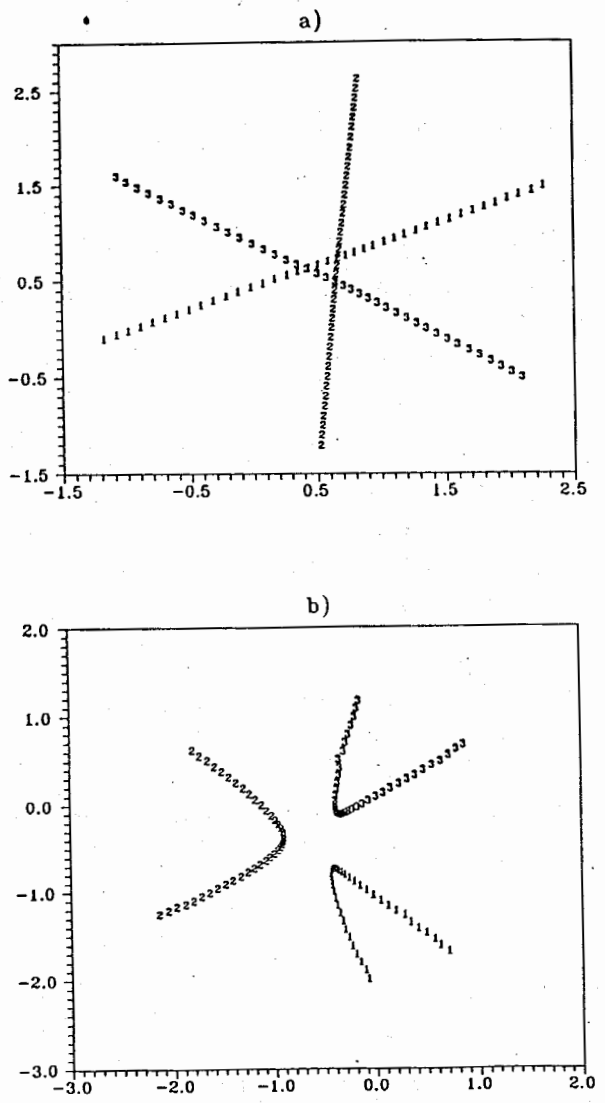


Fig.9 The result of mapping of three linear clusters from 5-dimensional space into 2-D one. The lines do not cross each other in 5-D.
a) The Niemann algorithm was applied,
b) The algorithm with pre-clustering of data used



The non-coherency of the mapped N-dimensional and transformed low-dimensional Euclidean spaces is **the second and main source** of **inevitable artifacts**. This sort of artifacts produced by the non-linear mapping do not depend on the chosen minimization technique. In **Fig.9a** the effect of spaces non-coherency is shown. The skew lines in the five-dimensional space cross each other in the two-dimensional one.

The authors believe that the mapping can only support an operator in clusters analysis, enabling him the direct view into their structure, but cannot substitute clustering. There exist many better and more sensible methods for clusters extraction than discerning them directly from disfigured patterns produced by the mapping techniques.

**The mapping should supplement the clustering and *vice versa.***

Because, the low-dimensional configuration ω' should reflect the clusters structure of the high-dimensional input data, the results of clustering can help to overcome the problem of initial configuration for mapping algorithms (stated above), giving valuable information about the global minimum of "energy" function. To force the appearance of resulting clusters in the ω', the artificial disturbance of the input squared distances array is introduced. The method (proposed by the first author) based on pre-clustering of data and clusters shrinkage factor K introduction for the clusters visualization (assuming high non- coherency between mapped and target spaces) can help to overcome partly the non-coherency problem. As is shown in **Fig.8c** good results were obtained, even better than those obtained using TA algorithm. Moreover, the computational time is much lower than that for TA approach. **Fig.9b** shows how the algorithm works in the presence of inevitable space non-coherence.

## 5. THE NEAREST FUTURE INVESTIGATIONS PLANS

In this short overview we do not touch on the problem of measurement error representation and its influence on clustering and mapping (mis - classification problem). This problem is under consideration. Some ideas will be stressed here only.

As show **Figs.7,** a single measurement with components disturbed by the random noise can be represented as hypersphere with a given radius. The mapping picture will consist of rings instead of points. We expect to obtain

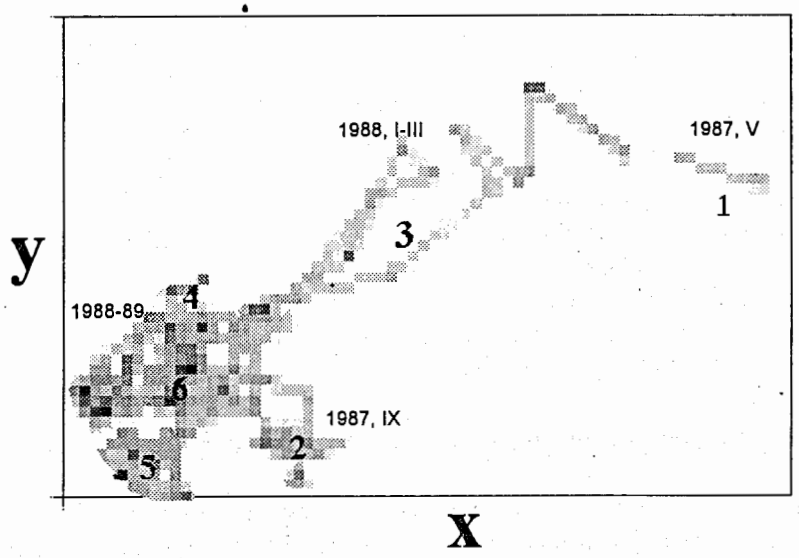


**Fig.10.** The mosaic diagram of 2-D mapping pattern reflecting the cluster structure determined by the 257-dimensional points representing PSDs of IBR-2 nuclear reactor during one and a half year operation period after moving reflector replacement

the mapping result (ω') like that presented in **Fig.10** being the mosaic map of the earlier result (without error assumed). Too high dimension of incoming data is the next problem which must be solved. Some of, e.g., frequency components, are useless and are the sources of misclassification errors. The computer experiments are being carried out to answer the question: How does the spurious, additional, randomly generated dimensions influence the clustering and mapping results?

The genetic algorithm approach (introduced first by Holland) will be testified (as a different one than simulated annealing and neural network approach to the global optimization problem) for diagnostic decision making and principal data extraction. Taking advantage of the network resources (i.e. distributed computing) to speed up calculations must be accomplished ultimately in the nearest future.



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