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APPLICATION OF PATTERN RECOGNITION TECHNIQUES TO THE DETECTION OF THE PHENIX REACTOR CONTROL RODS VIBRATIONS

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ABSTRACT

The incipient detection of control rods vibrations is very important for the safety of the operating plants. This detection can be achieved by an analysis of the peaks of the power spectrum density of the neutron noise. Pattern Recognition techniques were applied to detect the rod vibrations which occured at the fast breeder Phenix (250MWe).

In the first part we give a description of the basic pattern which is used to characterize the behavior of the plant. The pattern is considered as column vector in n dimensional Euclidian space where the components are the samples of the power spectral density of the neutron noise.

In the second part, a recursive learning procedure of the normal patterns which provides the mean and the variance of the estimates is described.

In the third part the classification problem has been framed in terms of a partitionning procedure in n dimensional space which encloses regions corresponding to normal operations.

This pattern recognition scheme was applied to the detection of rod vibrations with neutron data collected at the Phenix site before and after occurence of the vibrations.

The analysis was carried out with a 42-dimensional measurement space. The learned pattern was estimated with 150 measurement vectors which correspond to the period without vibrations. The efficiency of the surveillance scheme is then demonstrated by processing separately 110 measurement vectors recorded during the rod vibration period.

INTRODUCTION

During the past decade an extensive effort was made in the field of nuclear energy to develop methods able to achieve the surveillance and the diagnostic of the components of nuclear plants. The surveillance problem consists in classifying the operating modes in two classes : normal and abnormal. The diagnostic problem needs the identification of the causes of abnormality. This paper will be focused mainly on the resolution of the surveillance problem based on pattern recognition techniques. Pattern recognition techniques are widely applied to detect incipient failure of nuclear reactor components [1] - [4]. A surveillance system based on such a technique is reduced to characterize normal behavior and then to evaluate limits for abnormality.

Noise analysis techniques are applied to extract information from signal fluctuations. It could be shown that main failures detected on nuclear plants, such as loss of core mechanical integrity, loss of fuel element cooling or control rod drive mechanism failure induce changes in the random fluctuations of the neutron flux, coolant flow, pressure and displacement sensors.

The aim of this paper is to develop a method able to provide assistance to plant operators after a convenient data reduction and data processing. The method proposed utilizes results obtained by Piety [5]. The basic pattern is considered as column vector in an n-dimensional Euclidian space where the components are the samples of the power spectral density of the neutron noise. A recursive learning procedure of the normal pattern was chosen to estimate the mean and the variance of the normal pattern. The classification problem has been framed in terms of partitionning procedure in n-deimensional space and hyperellipsoïdes were retained as tha partionning surfaces. The original pattern is transformed by a change of coordinates defined by the eigenvalues of the covariance matrix. A statistical measure of distance is then defined to separate normal and abnormal patterns. Finaly the method establishes alarm thresholds in accordance with false alarm criteria determined by the plant operator.

The performance of the pattern recognition method was evaluated with neutron noise data recorded at the Phenix plant to detect the malfunction of one control rod. As it will be demonstrated, the influence of this failure was not able to be detected by the instrumentation installed at the plant.

PROBLEM FORMULATION

The aim of this study was the development of a surveillance method which utilize s noise analysis techniques and which can be implemented on a mini-computer. Figure 1 represents the block diagram of the surveillance system based on pattern recognition techniques. The raw data conditionned first by the data acquisition system, are processed to construct the pattern. For the Phenix data, the processor is based on the Fourier analysis and a Fast Fourier Transform algorithm provides the discrete power density function : A(fi), i = 1...n, where f_1 ..... f_n are frequencies uniformly distributed in the interval (0 - 16 Hz). The pattern which characterizes the behavior of the plant is represented by an n-dimensional column vector denoted X, where the components are the $A(f_c)$.. The output of this processor is then fed into the pattern recognition system in order to verify the normality of the updated computed pattern

The remainder of this paper is devoted to the description of the design of the pattern recognition system. The first task of the system is to learn the parameters which represent the normal behavior of the nuclear plant. This must be done automatically without operator assistance.

Once the initial learning is completed, the new patterns are analyzed to detect significant changes in the data characteristics during the pattern recognition step. A message of abnormality will be automatically displayed to the operator, according to an a priori false alarm probability criterion.

LEARNING PROCEDURE

The learning procedure is undertaken before the recognition step. During an observation period, the surveillance system learns what is the normal behavior by an analysis of the noise characteristics. This analysis leads to a statistical description of its normal behavior. For the Phenix case a recursive algorithm was applied to evaluate the mean and the covariance matrix of the learned pattern. The procedure is the following :

Let N be the number of spectra evaluated with the Fast Fourier Transform algorithm and $X_K = [x_{1k}, x_{2k}, \dots x_{nk}]$, the vector number K.

The mean vector M_{k+1} after k+1 computations is given by :

$$M_{k+1} - M_k + \frac{1}{k+1} [X_{k+1} - X_k]$$

The covariance matrix C_{k+1} of the (k+1) vectors is evaluated by :

$$C_{k+1} = \frac{1}{k+1} [X_{k+1} - M_{k+1}] [X_{k+1} - M_{k+1}]^T + \frac{k}{k+1} [C_k - X_{k+1} X^T_{k+1}]$$

The knowledge of M_n and C_n will be later used to check the Gaussian distribution of the set of observed vectors. After this observation period which yields the learned pattern, two procedures can be used. The first procedure, referred to as the supervised learning procedure does not take into account any extra data to improve the learned pattern. The second procedure, called adaptative learning method, is updating the learned pattern every time a new normal pattern is detected. The first procedure only is considered in this study. Once this learning period is completed the surveillance system monitors the new observed set of data and indicates the occurence of an anomaly.

PATTERN RECOGNITION PROCEDURE

This procedure will serve to determine if a new observed pattern corresponds to a normal or abnormal behavior. Simple and sensitive recognition schemes have to be designed to achieve rapidly the surveillance. To solve the specific problem of the Phenix control rod vibration, the classification problem of the pattern was solved by considering a region in n-dimensional space. To characterize the domain of normality, hyperellipsoïdes were chosen as particular surfaces. These surfaces are constructed with the initial vector X_k and have for equation :

$$(X_k - M_N)^T C_N^{-1} (X_k - M_N) = G_k^2$$

where M_N is the mean vector estimated during the learning period, and C_N is the associated covariance matrix.

The value of the constant G_k^2 determines the volume enclosed inside the surface. The eigenvectors and eigenvalues of the covariance matrix C_N give respectively the principal axes of the hyperellipsoïdes and the variances along the axes. The recognition procedure consists in determining the average volume characterizing the normal behavior and in checking if a given vector X_k is inside the hyper-ellipsoïd.

The pattern recognition problem can be interpreted as a measure of similarity between surfaces. In particular, the value G_K can be interpreted as a measure of the distance between the mean vector M_N and the observed X_k. In practice, as shown by Piety [5], the original Euclidean space is not the optimal space since the covariance matrix is not diagonal and consequently the elements of vector X_k may be correlated. In order to decorrelate the components of a vector X_k a decoupling transformation matrix Φ is suggested, such as X_k is transformed into Y_k. as $Y_k = \Phi X_k$

If the rows of Φ are normalized eigenvectors of the covariance matrix C_N, the transformed covariance matrix $\hat{C}_N$ of the transformed vector Y_k is a diagonal matrix whose elements $\hat{C}_{kj}$ represent the variances $\hat{\sigma}^2_{kj}$ along the transformed coordinate direction. This result is valid only when the data are Gaussian and a statistical test has to be made to verify this property. An interesting result associated with the découpling transformation is that the volume included in the hyperellipsoïdes remains identical :

$$(X_k - M_N)^T \quad C_N^{-1} \; (X_k - M_N) = (Y_k - \hat{M}_N)^T \; \hat{C}_N^{-1} \; (Y_k - \hat{M}_N) = G_k^2$$

where $\hat{M}_N$ represents the mean vector of Y_k, $k = 1 \ldots N$
$\hat{C}_N$ is the covariance matrix of Y_k.

G_k^2 can also be expressed by : $\quad (X_k - M_N)^T \; \Phi\Phi^T \; (X_k - M_N)$

Moreover, if the initial data set is Gaussian the transformed data set is also Gaussian. This hypothesis was tested for the Phenix case by using the Kolmogorov-Smirnov goodness-of-fit test. In practice, the Gaussian hypothesis was tested by checking that the variable Z defined by :

$$Z = (X - M_N)^T \; C_N^{-1} \; (X - M_N)$$

is a random variable having a distribution function of a CHi-Square variate with n degrees of freedom (n : number of components of vectors Y_k and Y_k). One sample of the Kolmogorov-Smirnov variable is expressed by :

$$D = \max_Z |F_N(Z) - F(Z)|$$

D is the maximum of the differences between the postulated and measured distribution functions, $F_N(Z)$ is the calculated distribution function of Z, F(Z) is the Chi-Square distribution function of a variable with n degrees of freedom.

The Kolmogorov-Smirnov goodness-of-fit test considers that the hypothesis that the sample set is governed by the assumed density function is true if $D < D(\alpha, N)$, where α is the significance level. The values of $D(\alpha, N)$ such as $P(D > D(\alpha, N))$ are tabulated for various values of N and α in [6].

The surveillance problem consists in determing if a particular measurement belongs to the mean of the data set. This is accomplished by calculating the term G_k^2 and the decision is made by comparing the value obtained to a preassigned threshold S_o. The determination of a value S_0 for a specified false alarm probability, requires in the general case the exact knowledge of the probability density function of Z. For an n-variate Gaussian distribution with known mean vector M_N and covariance matrix C_N, the variable $Z = (X_k - M_N)^T C_N^{-1} (X_k - M_N)$ is a Chi-Square variate with n degrees of freedom. Let α be the false alarm probability acceptable for the surveillance system. The hyperellipsoïde specified by :

$$(X_k - M_N)^T C_N^{-1} (X - M_N) = \chi^2 (1 - \alpha)$$

will enclose 100α% of the multivariable population.

For instance, if $n = 40$ and $\alpha = 0.05$, the hyperellipsoïde is defined by $Z = 55.8$.

For a false alarm probability α, the observed pattern X_k will be classify as normal when $Z_k < \chi^2(1 - \alpha)$, otherwise the pattern is considered as non acceptable and an alarm is activated.

APPLICATION TO PHENIX DATA

The performance of the surveillance scheme was evaluated to detect a control rod malfunction which occured at the Phenix site. This fast breeder sodium cooled reactor has a 250 MWe power. It is located in Marcoule in the south of France. The raw data are the neutron fluctuation given by the neutron detector. These fluctuations were amplified and recorded on an analog tape recorder to be processed off-line on the surveillance system, implemented on a minicomputer. Two sets of signals were recorded on the plant : the first set corresponds to the normal behavior of a control rod, the second set was observed after the failure of a control rod.

The power spectral density was computed with and without failure. The set of power density spectra without anomaly constituted the learning set and 150 PSDs were evaluated during this learning period. The abnormal set of PSDs contained 119 PSDs. Each pattern X_k was formed by a vector with 42 components form 0.4 Hz to 16.8 Hertz at 0.4 Hz interval.

Figure 2 represents the 30 first normal PSDs. Figure 3 shows the 30 first abnormal PSDs. These two plots demonstrate that it is impossible to visually detect an abnormaly and consequently a pattern recognition scheme must be used. The surveillance system was first trained with 150 PSDs and in figure 4 the shape of the mean vector is represented. The covariance matrix C_{150} was recursively computed according to the procedure described previously. The Kolmogorov-Smirnov goodness-of-fit test was applied to check the Gaussian properties of the data. The histogram of the density probability function of Z was evaluated and is plotted in figure 5.

Table 1 gives the theoretical and computed repartition of the Chi-Square variable with 42 degrees of freedom and the absolute value of the difference $|F_N(Z) - F(Z)|$

χ^2	F	$F_N(Z)$	$\lvert F_N(Z) - F(Z)\rvert$
22.2	0.005	0.008	3.10^{-3}
23.7	0.01	0.013	3.10^{-3}
26.	0.025	0.018	7.10^{-3}
28.2	0.05	0.031	$1.9.10^{-2}$
30.8	0.10	0.082	$1.8.10^{-2}$
35.5	0.25	0.256	6.10^{-3}
41.3	0.50	0.547	3.10^{-3}
47.7	0.75	0.781	$3.1.10^{-2}$
54.	0.90	0.926	$2.6.10^{-2}$
58.1	0.95	0.960	$1.0.10^{-2}$
61.7	0.975	0.991	$1.6.10^{-2}$
66.2	0.99	0.994	4.10^{-3}
69.3	0.995	0.995	0

TABLE 1 : Values of F and $F_N(Z)$

To check the pattern normality during the recognition procedure, a false alarm probability was chosen equal to 0.05. The associated threshold S_o is 58.124 according to the χ^2_{48} (0.95) distribution. In order to obtain a satisfactorily detection rate of the abnormal patterns, it was necessary to compute the average of 5 consecutive Z_k before the comparison to the threshold S_o. With this procedure among the 23 clustered sets, 4 failed the test and 19 were recognized as abnormal. With a false alarm probability equal to 0.1 all the patterns failed the test. The relative low sensibility of the surveillance scheme can be explained by the fact that the normal and abnormal patterns are very close together as it can be seen in figure 6 which represents the mean vectors for the normal and abnormal case.

The surveillance scheme and the associated algorithms were implemented on a 16 bit standard mini computer SOLAR 16-40 having 32 K memory size.

CONCLUSION

The experimental results obtained by the surveillance system with data collected at the Phenix site shows that pattern recognition techniques can be used to detect satisfactorily an abnormal behavior of a plant. In addition the surveillance can be easily implemented on a minicomputer.

Future work will test a larger data base in order to increase the sensitivity of the surveillance system. In addition, a portable surveillance system will be develop around a Hewlett Packard 9845 system coupled to an FFT analyzer.

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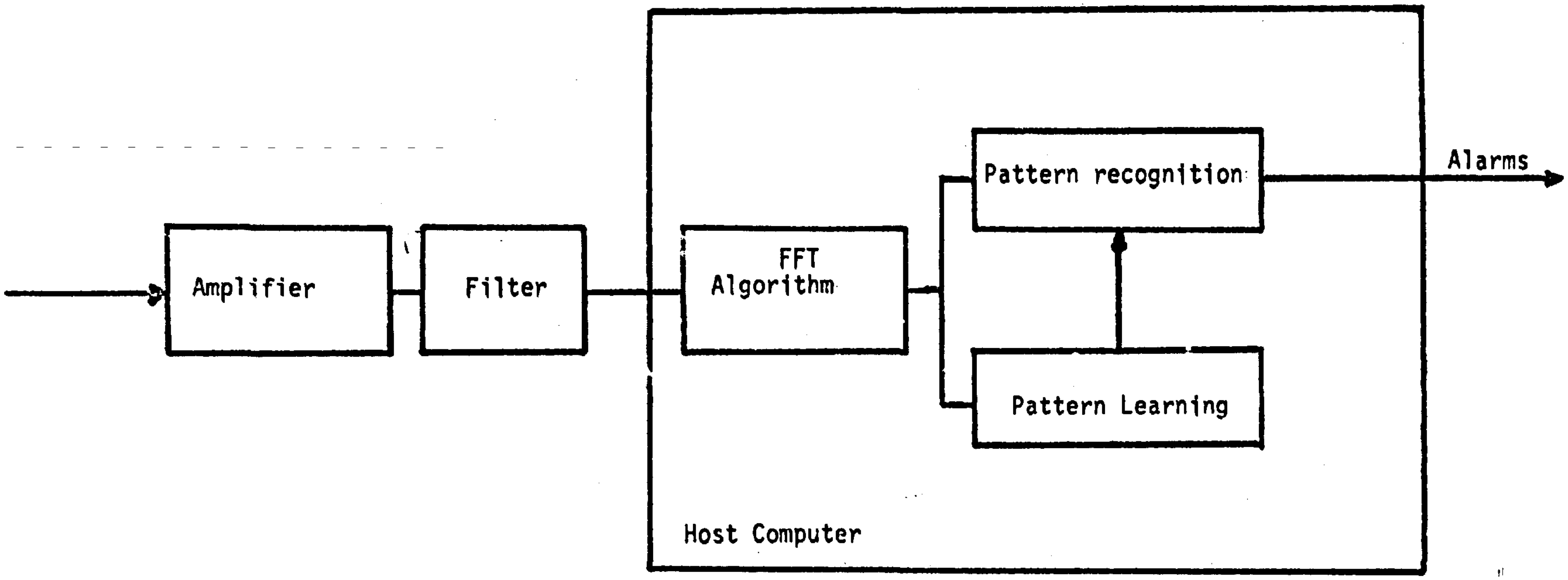

FIGURE 1 : DIAGRAM OF THE SURVEILLANCE SYSTEM

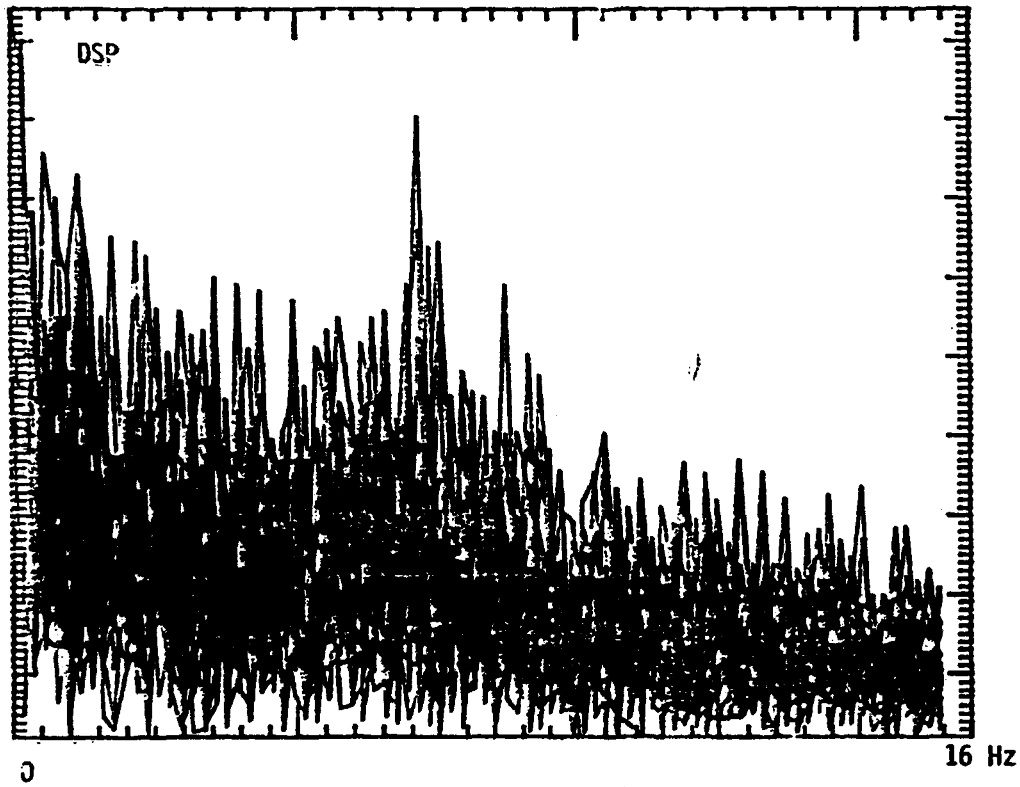

FIGURE 2 : 30 NORMAL SPECTRA

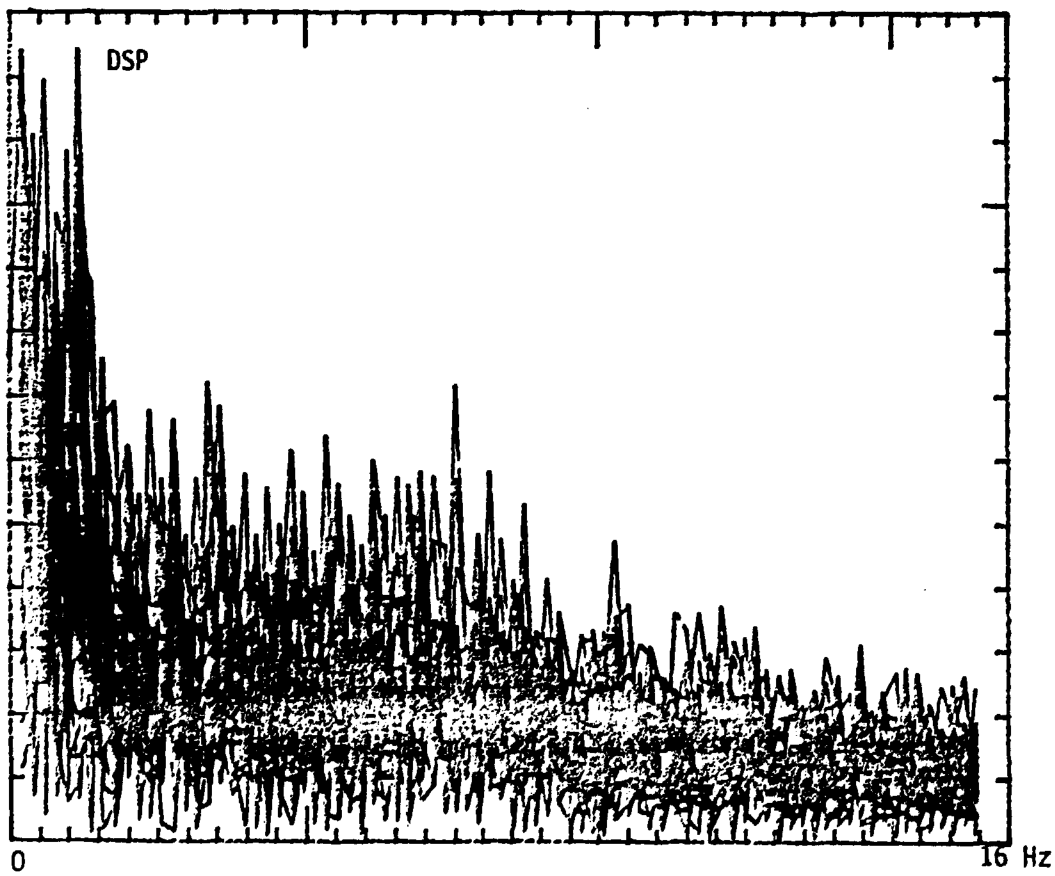

FIGURE 3 : 30 ABNORMAL SPECTRA

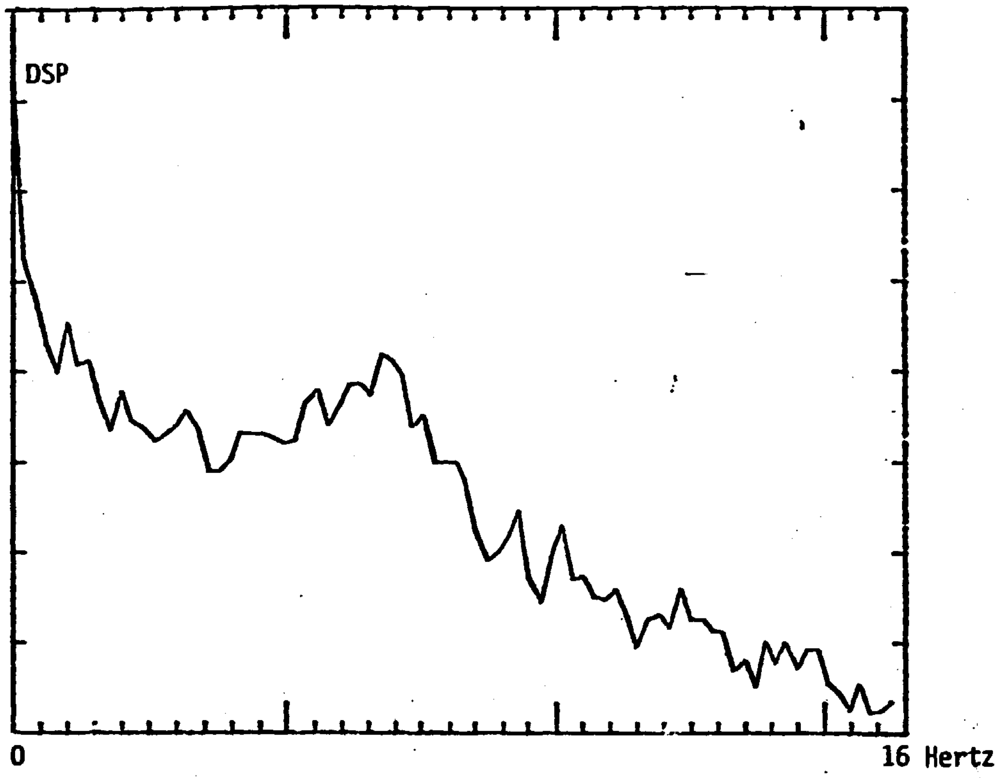

FIGURE 4 : MEAN SPECTRUM OF 150 ELEMENTS

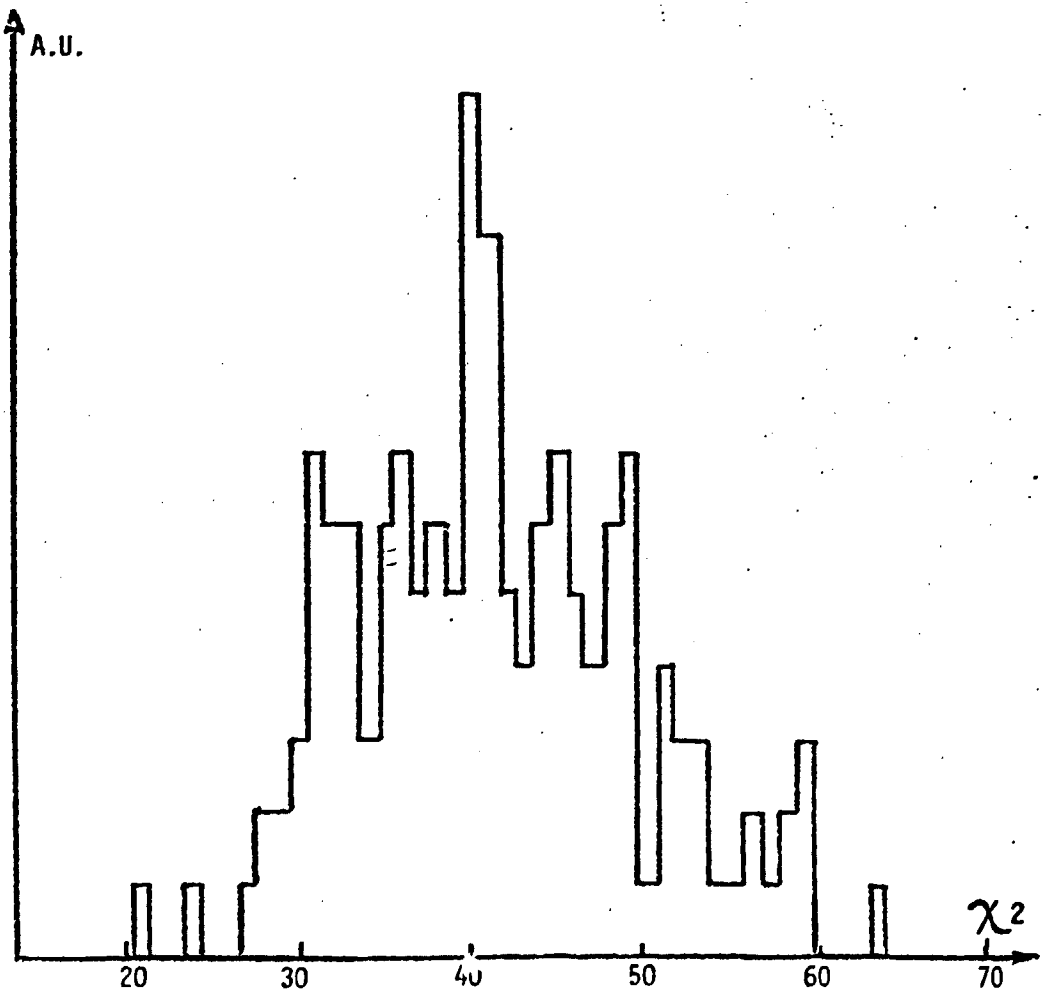

FIGURE 5 : HISTOGRAMM OF THE PROBABILITY DENSITY OF Z

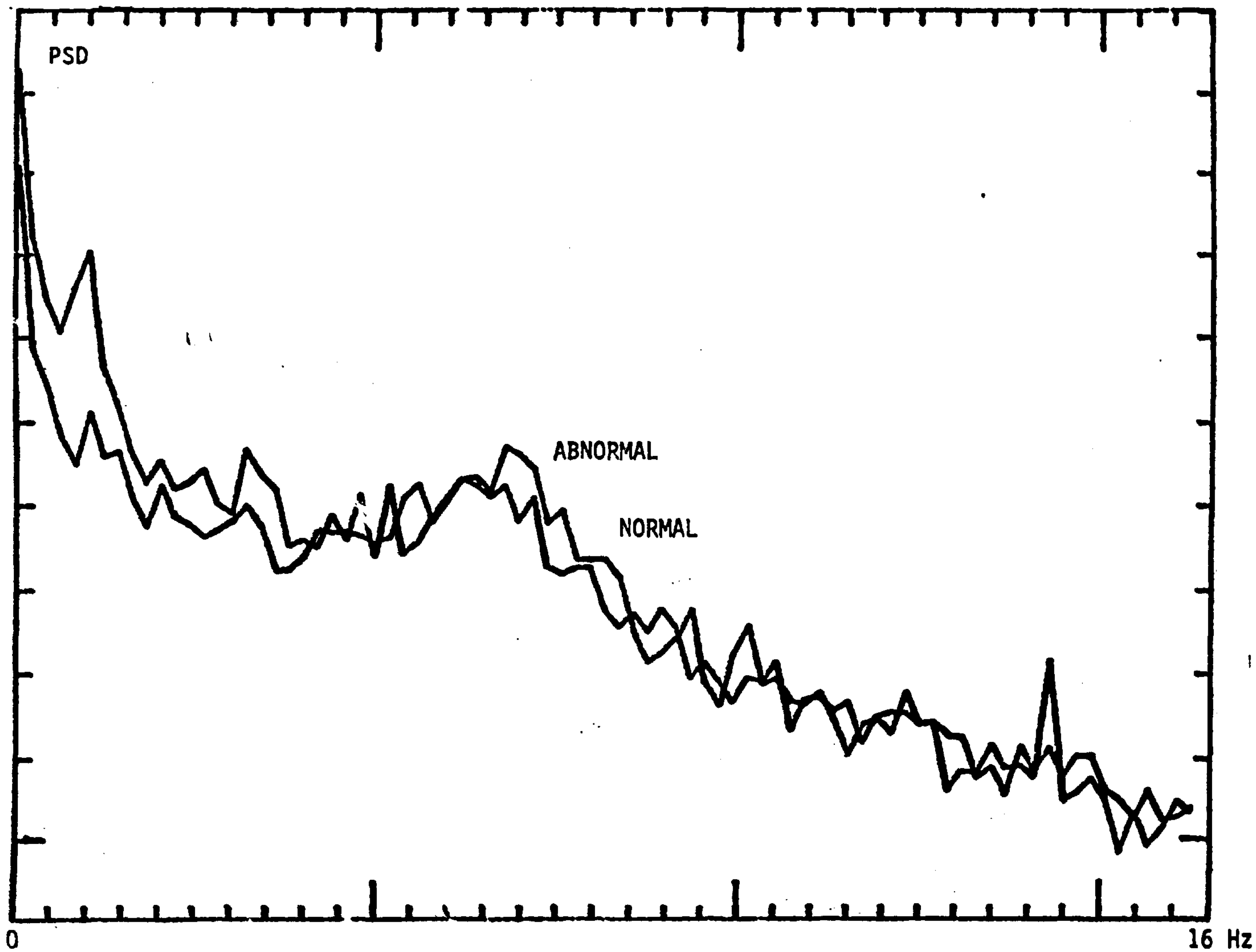

FIGURE 6 ; COMPARISON O F NORMAL AND ABNORMAL MEAN VECTORS