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SURVEILLANCE OF INDUSTRIAL PROCESSES WITH CORRELATED PARAMETERS

Abstract

A system and method for surveillance of an industrial process. The system and method include a plurality of sensors monitoring industrial process parameters, devices to convert the sensed data to computer compatible information and a computer which executes computer software directed to analyzing the sensor data to discern statistically reliable alarm conditions. The computer software is executed to remove serial correlation information and then calculate Mahalanobis distribution data to carry out a probability ratio test to determine alarm conditions.

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Government Interests

This invention was made with Government support under Contract No. W-31-109-ENG-38 awarded by the Department of Energy. The Government has certain rights in this invention.

Description

The present invention is related generally to a method and system for carrying out on-line surveillance of industrial processes with correlated sensor parameters. More particularly, the invention is concerned with a method and system for processing sensor data as an improved methodology over a basic SPRT approach to industrial process surveillance. Further, the invention can be used as part of an improved SPRT analysis itself.

Conventional parameter-surveillance schemes are sensitive only to gross changes in the mean value of a process or to large steps or spikes that exceed some threshold limit check. These conventional methods suffer from either large numbers of false alarms (if thresholds are set too close to normal operating levels) or a large number of missed (or delayed) alarms (if the thresholds are set too expansively). Moreover, most conventional methods cannot perceive the onset of a process disturbance or sensor deviation, which gives rise to a signal below the threshold level for an alarm condition. Most methods also do not account for the relationship between a measurement by one sensor relative to another sensor measurement.

In another monitoring method, the conventional SPRT technique has found wide application as a signal validation tool in the nuclear reactor industry. The SPRT method is a pattern recognition technique that processes the stochastic components associated with physical process variables and has high sensitivity for the onset of subtle disturbances in those variables. Two features of the SPRT technique make it attractive for parameter surveillance and fault detection: (1) early annunciation of the onset of a disturbance in noisy process variables, and (2) the SPRT technique has user-specifiable false alarm and missed-alarm probabilities. SPRT techniques

are primarily directed to the analysis of data from paired or multiple pairs of sensors to contrast to a large number of difference process sensor data points. SPRT is also typically dependent on assumptions of the data being independent and being Gaussian distributed data.

It is, therefore, an object of the invention to provide an improved method and system for surveillance of industrial processes.

It is another object of the invention to provide a novel method and system for on-line surveillance of industrial processes with correlated parameters.

It is also an object of the invention to provide an improved method and system for evaluation of industrial process data, on-line or off-line, from unpaired sensors.

It is a further object of the invention to provide a novel method and system for performing preliminary analysis of sensor data for alarm conditions prior to data input to an SPRT system.

It is an additional object of the invention to provide an improved method and system for carrying out elimination of serial correlation information from sensors prior to performing tests for abnormal process conditions.

It is still another object of the invention to provide a novel method and system for removing serial correlation of sensor data taken in an industrial process by at least one of the following: (a) eliminating Fourier components selectively, and (b) using auto correlation structure present in the data from each of the sensors.

It is yet a further object of the invention to provide an improved method and system for processing sensor data free from serial correlation effects using calculated Mahalanobis distances.

It is also an additional object of the invention to provide a novel method and system utilizing an empirical test data distribution for deriving the likelihood of observing different Mahalanobis distances.

It is also another object of the invention to provide a novel method and system for comparing industrial process training data to on-line industrial process data by calculating comparative Mahalanobis distances for each data set.

It is still another object of the invention to provide a novel method and apparatus for statistically analyzing data from an industrial process using time averaged or skipped data to bypass slowly changing data.

It is yet a further object of the invention to provide an improved method and system using statistical information including use of a linearized variable technique (i.e., use of a variable whose behavior is, over the whole range a nonlinear behavior, but which can be modeled as many increments of linear variable responses).

It is an additional object of the invention to provide an improved method and system for isolating single bad sensors by calculating a Mahalanobis distance with the bad sensor being masked or

by determining the sensor whose expected value (given the other sensor values) is furthest from the actual value.

The features of the present invention that are believed to be novel are set forth with particularity in the appended claims. The invention, together with the further objects and advantages thereof, may best be understood by reference to the following description taken in conjunction with the accompanying drawings, wherein like reference numerals identify like elements.

Brief Description of Drawings

FIG. 1 shows a block flow diagram of a system for implementing an industrial process surveillance system;

FIG. 2 illustrates a generalized block flow diagram of the data analysis performed using a surveillance system constructed in accordance with the invention;

FIGS. 3A-3F encompasses a detailed block flow diagram of the analysis shown in FIG. 2 where FIG. 3A corresponds to general box A in FIG. 2; FIG. 3B corresponds to the general box B in FIG. 2; FIG. 3C corresponds to the general box C in FIG. 2; FIG. 3D corresponds to the general box D in FIG. 2; FIG. 3E corresponds to the general box E in FIG. 2 and FIG. 3F corresponds to the general box F in FIG. 2; and

FIG. 4A shows a Mahalanobis distance calculation and FIG. 4B shows a transformed Mahalanobis calculation to principal components.

Detailed Description of Preferred Embodiments

A system constructed in accordance with the invention is indicated generally at 10 in FIG. 1. As shown therein, a surveillance portion (12) is performing monitoring operations on an industrial system (14) by means of a plurality of sensors (16) that can sense raw data information characteristic of a wide variety of variables, such as, temperature, flow rate, pressure, chemical composition, biomedical information, density, shaft rotational speed, electrical power level, electrical phase, electrical frequency and other such process variables.

It is typical in the industrial system (14) that a substantial degree of cross correlation exists among sensed data from the plurality of sensors (16). In many industrial processes such cross correlation arises naturally from the physics or chemistry inherent in such systems. For example, if the industrial system (14) involves fluid transport, then the flow rate, pressure drops and upstream versus downstream temperatures will all have a substantial degree of correlation. A further example for the industrial system (14) is for rotating machinery wherein the rotation of a shaft will generate a rotational-speed signal, which is highly correlated with the power provided to drive the machine motor. Further, both of these variables are usually correlated with radial vibration levels for the machine. If the industrial system (14) includes an array of the sensors (16) deployed to measure the same variable, there can be a high degree of correlation due to the close proximity of the various sensors (16).

The system (10) is operated by use of a conventional computer (17) executing a computer software package (SMP software package hereinafter), which is embedded in a storage medium on board the computer (17), and a copy of the best mode is attached hereto as a source code appendix. This mode can be extended using additional methodologies described

hereinafter using conventional algorithms and commercially available computer software programs. Further details will be mentioned, when appropriate, in later descriptions. The system (10) also includes a conventional interface DAQ board (19) and a signal conditioning module (15) (e.g., a model number SCRI 1120 or 1200 made by National Instrument Corp). The DAQ board (19) and the module (15) allow the raw data information from the sensors (16) to be converted to computer data usable by the computer (17).

The SMP software package generally processes computer analyzable sensor data in three stages (see FIG. 2). The first stage is concerned with elimination of serial correlation signals. Serial correlation refers to the correlation in time of signals from a particular sensor with itself. Cross correlation refers to the correlation between two sensors at the same or different times. This first stage of the processing minimizes the overall false alarm occurrence for the system (10). The serial correlation can be removed by one of two user-selectable methods: (1) eliminating Fourier components (individual frequencies or bands can be removed), or (2) by using the autocorrelation structure present in the data. There is also a provision for allowing the autocorrelation and/or the power spectrum to be recalculated and compared with earlier results. The assumption that the data follow a multivariate normal distribution can be made throughout. However, even if a normal distribution does not characterize the data, the test will generally yield statistically good results. The conventional Pearson product moment correlation can be used as an estimator for the true correlation.

The second stage of processing is one in which the Mahalanobis distance (a metric) is calculated for training data (data obtained knowing all sensors are good and the process is properly functioning for the industrial system (14) for all time points after transformation to eliminate serial correlation. The cumulative distribution function (CDF) of the Mahalanobis distance is computed, and from this distribution a probability distribution function (PDF) can be formed. Similar distributions can be created for the multiple situations in which each individual sensor is masked from the computations and also for different regimes of segmented variables and for averages or skipped-time points. A provision exists for recalculation of all distributions at later times to ensure that there has been no significant drift.

The final or third stage of processing employs a probability ratio test of the distribution data to determine if there is sufficient evidence to annunciate a warning. This test includes, as an option, the capability to set the test statistic to zero whenever it becomes negative. This enhances the sensitivity of the test and is mathematically equivalent to starting a separate test at each time point.

In order to operate the system (10), as shown in FIG. 2 and in more detail in FIG. 3A, the SMP software package is used by a system operator who inputs a number of correlated variables via a conventional input device, such as a keyboard (20). The operator also can enter a desired number of process-system training data points, which provide a standard of reference for a properly operating form of the industrial system (14). In addition, the operator can choose to implement, or skip, the third and fourth illustrated steps in FIG. 3A. In the third optional step, selected points can be skipped or in the fourth step a set of data can be linearized as described hereinafter.

As shown in FIG. 3B, the operator then can select one of the options to implement the first stage: (a) use of Fourier filtering, (b) uses of auto-regressive filtering, (c) combinations of “a”

and “b”, and (d) no filtering. Steps “a” and “b” are therefore used for removal of any self-correlation information from the sensor (16).

If the operator has selected option “a” above, a Fourier transform is performed on the data (see lower part of FIG. 3B). A fast Fourier transform (FFT) is used to determine the amplitude, phase, and power spectrum of a series of training points. Such an FFT can be easily accomplished by conventionally available computer subroutines (see appendix). The Fourier components are those determined using the expression:

$$X_f = \sum_{t=0}^{N-1} x_t e^{2\pi it/N} \tag{1}$$

where x_t is the value of x at time t, and N is the total number of points. The coefficient X_n is complex and because the time values are real, it is symmetric. The power at a given frequency is determined using the following:

$$P_F = \frac{|x_f|^2}{N^2} \tag{2}$$

where the subscript f denotes a particular frequency. The preferred SMP software package for performing FFT analysis (see appendix) allows the user to specify a particular frequency that he wants removed. It also allows the user to specify a band within which he wants the top M powered frequencies removed (where M is an integer that is also specified by the user). The removal of self-correlation via FFT analysis occurs via simple superposition (see FIG. 3D). That is, the user of the FFT subroutine is permitted to select up to eight Fourier components for removal, and the Fourier components are removed by determining the phase and subtracting the corresponding amplitudes with the given phases from the signal. The relative phase is determined directly from knowledge of when the training data were taken and of when the sampling began for the data to be tested. If this interval is uncertain, the SMP software package re-computes the phases using the first set of actual data.

The code can be further enhanced to allow the user to run multiple tests simultaneously; this corresponds to the third item in FIG. 3A. One of these tests would consider every point while the other would consider every n^{th} point (or the time average of N points). This would allow the code to detect gross errors that occur over large periods of time. There is little added complexity in doing this; the array storage must be modified and a simple selection or averaging routine must be added.

In addition, the code can be modified to periodically check that neither the Fourier components (i.e., the phase) nor the autoregressive coefficients have changed significantly. This corresponds to the first four items in FIG. 3F. If either has, the user is notified and is given the option to update these. Two methods are used to determine whether or not the change is significant. The first is a simple magnitude check, and the second involves the use of the distributional shape of the coefficients and an input number of standard deviations. The Fourier components and autoregressive coefficients are computed in the manner given above.

The code can be modified to ensure that the correlation matrix is periodically checked for significant changes. This corresponds to items 5 and 6 in FIG. 3F. These changes are detected using distributional knowledge (approximately chi-squared) and an input number of standard deviations. The user is notified of changes and is given the option to update the matrix. The Pearson product-moment correlation coefficients are used to estimate the true correlation coefficients.

The code can be modified to allow for two methods of determining a bad one of the sensors (16). The first is the method currently implemented in the code. This corresponds to items 2 and 4 in FIG. 3E. The second involves the use of the principal components to estimate the value of a parameter. The sensor (16) that is tagged as bad is the one whose measured value is furthest from the expected value given the other sensor readings.

If the operator elects the autoregression method (see top of FIG. 3B), the option is available to skip selected terms to reduce the amount of storage and computation required while still including higher order terms needed. As shown in FIG. 3C, the training data is then used to establish coefficients for the desired terms in the sequence and such autocorrelation coefficients can be found using coding (see appendix) that employs the Conventional Yule-Walker equations and well-known, commercially available subroutines from LINPACK (now LAPACK). These coefficients can be found in the following manner:

If one has a series of observations, x_i, the estimate of the lag "n" correlation is obtained using the following relation:

$$\rho_n = \frac{\sum_{i=1}^{N-\pi}(X(i+n)-\mu)(X(i)-\mu)}{(N-n)\chi_o^{\ 2}} \tag{3}$$

where X_o^2 is the estimated variance, and, μ is the estimated mean. Using this expression, the SMP software package determines the expected value of a future observation, given the past observations. This is done using the equation

$$Y(n) = X(n) - a_n^{\ T} \sum_{n-1}^{-1} X_{n-1} \tag{4}$$

where

$$a_n^{\ T} = [\chi_{n-1}\chi_{n-2}\cdots\chi_2\chi_1],$$

$$\sum_{n-1}^{-1} = \begin{bmatrix} x_0 & x_1 & \cdots & x_{n-2} & x_{n-1} \\ x_1 & x_0 & \cdots & x_{n-3} & x_{n-2} \\ x_{n-2} & x_{n-3} & \cdots & x_0 & x_1 \\ x_{n-1} & x_{n-2} & \cdots & x_1 & x_0 \end{bmatrix}^{-1}$$

$$X_{n-1} = \begin{bmatrix} X(1)-\mu \\ X(2)-\mu \\ X(n-1)-\mu \end{bmatrix}$$

X_n is the lag n covariance, and, Y(n) is the nth innovation.

The value for Y_n is the conditional expectation when the underlying distribution is assumed to be multivariate normal. Under reasonable statistical assumptions, it is independent from previous observations and therefore satisfies the requirement of an input variable to a SPRT analysis. Further details of SPRT analysis and related matters can be found in U.S. Pat. No. 5,410,492, which is incorporated by reference herein in its entirety.

A provision exists in the package to recalculate the autocorrelation after a fixed number of observations. This can be compared with the original result and if there is a significant change, the user can decide to accept or reject the new results (see FIG. 3D and 3F).

The SMP software package allows for the superposition and mathematical manipulation of the two serial correlation reduction methods (see FIG. 3B). When performing this calculation, one must be mindful of the creation of data set innovations that can influence the spectrum; and the elimination of the certain spectral components can change the autocorrelation. The most preferred method of using this methodology is to use the innovations to eliminate the high frequency components and then use the Fourier transform to remove the low frequency components.

Whether one chooses the Fourier transform method, autoregression, or no filtering at all, training data can be used to compute principal components (see FIG. 3C) by an eigenvalue/eigenvector calculation using the computer software methodology set forth in the appendix.

In the first stage of processing using the SMP software package, the variables were treated one at a time with no regard for the correlation that exists between the sensors (16). In the second stage of the processing the presence of the correlation is actively utilized. As shown in FIGS. 3C-3E, this is accomplished by computing the Mahalanobis distance, and this distance is defined as:

$$d = \left(\chi_i - \bar{\chi}\right)^t S^{-1} \left(\chi_i - \bar{\chi}\right) \tag{8}$$

where

$$S = \frac{1}{(n-1)} Y^t Y \tag{9}$$

and Y is an n by p matrix whose rows are $(X_i - X)^T$. <u>NOTE – Second chi should have bar above it to represent mean value.</u>

The Mahalanobis distance can be viewed more clearly if a transformation is made to principal components. This transformation is illustrated pictorially in FIGS. 4A and 4B. The first principal

component is the direction in which the maximum amount of the variation occurs. As can be seen from the Figure, this is in the S.sub.1 direction. A measure of the distance which any point lies from a previous data set can be derived by weighting the squared difference from the mean by the inverse of the standard deviation in that direction, i.e., for directions in which there is large variation in the data. Therefore, large standard deviations, a value far from the mean, would not necessarily result in a large Mahalanobis distance. Conversely, for directions in which there was little variation in the training data, and therefore small standard deviations, a value far from the mean would result in a large Mahalanobis distance. As a result, points which fall in the same pattern as those in the training set would have lower Mahalanobis distances.

In the most preferred embodiment, the Mahalanobis distance is calculated for each time point during the training period. From this information a cumulative distribution function F(di) is estimated using

$$F(d_i) = \frac{(\text{number of observations} \le d_i) - 0.5}{\text{total number of observations}} \tag{10}$$

The slope of this function is then used to determine the likelihood function for the Mahalanobis distance. If one of the sensors 16 goes bad, this distance will increase a statistically significant amount.

The average Mahalanobis distance is also calculated for the case in which one of the sensors 16 is masked (see FIG. 3E). This facilitates the determination of the bad sensor 16. The Mahalanobis distance will be closest to that found in the training data when the bad sensor 16 is masked. In the preferred SMP software package, the capability for discerning a single bad sensor is provided. The capability for extending this to multiple bad sensors 16 using a similar methodology, or a binary search algorithm, is also included as an option for the SMP software package.

At this point, two hypotheses are considered for the incoming raw sensor signals or data information from the sensors 16 monitoring the industrial system 14: the null hypothesis, H0, that there is no signal abnormality is tested and the alternative hypothesis, H1, that there is an abnormal signal from one of the sensors 16 (see FIG. 3D). To perform this test, certain assumptions are preferably made concerning abnormal operations. In the SMP software package, one specifies a multiplier and offset for the Mahalanobis distance which would occur in the case of abnormal operation. This distributional shape is assumed to be the same as that for normal operation.

The following ratio is formed in this analysis:

$$P_n = \frac{\begin{array}{l}\text{Probability of Mahalanobis distance}\\ \text{sequence } (d_1, d_2 \ldots, d_n) \text{given } H_0\end{array}}{\begin{array}{l}\text{Probability of Mahalanobis distance}\\ \text{sequence } (d_1, d_2 \ldots, d_n) \text{given } H_1\end{array}} \tag{11}$$

which can be written as:

$$P_n = \prod_{i-1}^{n} \frac{f < d_1 \mid \varepsilon(H_0) >}{f < d_i \mid \varepsilon(H_1) >}$$

where $\xi(H_1)$ is used to designate the parameters present in the distribution function which correspond to either the null or alternative hypothesis.

The Wald Wolfowitz theory states that continued sampling should occur when $A<P_n<B$. The null hypothesis (no sensor error or fault) is accepted when $P_n>B$ and rejected if $P_n<A$. The values of the false alarm probability and nondetection probabilities are computed using direct Monte Carlo simulation (analysis preferably done off-line with simulated data) and will vary depending on the failure mechanism. The following relations govern the assignment of the values for A and B:

$$A = \frac{\beta}{1-\alpha}, \text{and}, B = \frac{1-\beta}{\alpha} \tag{13}$$

where α and β are the parameters which can influence the false alarm and nondetection probabilities and can be assigned using accepted statistical practice. This approximate equality has been shown to be correct in a wide range of problems, particularly when the values of α and β are small.

The test procedure, as described above, will give an annunciation that one of the sensors 16 has failed. This procedure will not, however, identify the failed sensor 16. As shown in FIG. 3E, to do this, the Mahalanobis distance sequence is computed for the cases in which one of the sensors 16 is masked. This fails for all cases except for the one in which the bad sensor 16 is masked. This method assumes that only a single one of the sensors 16 will fail. If this is not the case, the method can be extended, with significant additional calculational requirements, to multiple sensor failures.

In another form of the invention, a data set can be "linearized" as in FIG. 3A, the fourth step and the first item in FIG. 3C. In this embodiment, the correlation matrix and eigenvector (principal component vector) can be generalized so that it has several regimes for a given variable. The probability will be calculated using the Mahalanobis distance distribution which is computed using the eigenvectors for the particular linearized variable regime. An example of a linearized variable is the power of a nuclear reactor. The operating characteristics of such a reactor vary dramatically as the power is changed. The regimes can be used to linearize the problem. These regimes can also be used to turn off the test at times were it is not appropriate (e.g., startup or scrams).

As an example of application of the preferred technique, the effluent thermocouple sensors on the EBR-II (a nuclear reactor at Argonne National Laboratory Wes0 were monitored. The average sample number (the number of samples necessary before a determination could be made of whether the system 14 was normal or abnormal, typically about two to ten samples, "ASN" hereinafter) and false alarm probabilities (the probability that the test would indicate an abnormal state when an abnormal state did not exist in fact, "FAP" hereinafter) were computed as a function of parameters .alpha. and .beta. and the offset and multiplier of the Mahalanobis distance distribution. The results are given in Table 1. For this analysis, 8,000 time points, each

with twenty sensor values, were used. Of these, the first 7,000 were used for the principal component analysis ("PCA") and the next 1,000 points were used to determine the ASN, and also determine the FAP.

TABLE I – Average Sample Number (ASN) and False Alarm Probability (FAP) as a Function of Test Parameters.

α	β	Offset	Multiplier	ASN	FAP
0.001	0.001	0.0	2.0	10.00	68.0%
0.001	0.001	10.0	1.0	8.06	32.3%
0.001	0.001	10.0	2.0	3.57	9.3%
0.001	0.001	20.0	2.0	2.46	1.7%
0.01	0.001	10.0	2.0	3.45	12.4%
0.001	0.01	10.0	2.0	2.65	7.7%
0.001	0.001	20.0	4.0	2.38	0.5%

The FAP decreased when parameter β is increased, when the offset is increased, or when the multiplier is increased. This decrease occurs because these factors all increase the distance between H_0 and H_1, thereby decreasing the likelihood that H_1 will be chosen given H_0. The FAP is increased when parameter α is increased. The ASN decreases as H_0 and H_1 are separated because the likelihood ratio criterion is met more quickly when the two distributions are distinct. Using the above dependencies, it is possible to set the false alarm level to any desired value.

An analysis was also performed in which one of the signals from one of the sensors 16 was ramped at 0.1 standard deviations/me point using the parameters in the last line of Table 1. When this was done, it required thirteen time steps for the SMP software package to detect the abnormality. The SMP software package correctly identified the errant sensor 16 by comparing the Mahalanobis distances with one of the sensors 16 masked.

The method described hereinbefore using the Mahalanobis distance as a test statistic has been developed and has been demonstrated as a viable way of determining abnormal readings from the effluent thermocouple sensors 16 in EBR.II. This method, in general, also can incorporate the SPRT test methodology using an empirical distribution to determine probabilities.

The ability of this methodology to detect faults in the industrial system 14 is dependent on the variables having a significant correlation. This correlation results in a space where it is less likely to obtain observations. The rank of this space is determined by the total number of dimensions minus the number of dimensions in which the singular values are significant (>1.0% of the maximum eigenvalue). At the present time, there are nine significant values, which indicates significant correlation.

The invention is therefore able to carry out surveillance and detailed analysis of industrial processes to provide alarm notifications for statistically significant deviations from proper operating conditions. The invention has broad applicability for any system in which correlated individual sensors are present. These individual sensors can be at the same or different locations and can be measuring the same or different variables. The industrial system 14 can include without limitation a nuclear power station, fossil power stations, automobiles, aircraft,

shops, water and waste treatment facilities, manufacturing lines, pumping stations, environmental systems, gas lines, chemical processing systems, pharmaceutical manufacturing systems and biomedical systems.

While preferred embodiments of the invention have been shown and described, it will be clear to those skilled in the art that various changes and modifications can be made without departing from the invention in its broader aspects as set forth in the claims provided hereinafter.

Claims

What is claimed is:

1. A system for surveillance of an industrial process to assess at least one of an operational state of the industrial process and the operational state of sensors monitoring the process, comprising:

   at least one sensor means for sensing raw data information from the industrial process corresponding to the operational state of the industrial process;

   means for converting the raw data information to computer data;

   computer means for receiving the computer data and generating sensor data analyzable by the computer means;

   computer software means executable by the computer means for carrying out manipulation of the sensor data, said computer software means including, (a) means for removing serial correlation information between any of the means for sensing raw data information and (b) means for calculating Mahalanobis distribution data and determining a statistical deviation from previously accumulated training data for the industrial process, wherein the training data is characteristic of raw data information with the means for sensing operating normally and the industrial process properly functioning; and

   means for applying a probability ratio test to the Mahalanobis distribution data to determine alarm conditions for said industrial process and said sensor means.

2. The system as defined in claim 1 wherein said computer software means includes means for assuring the auto- and cross-correlation structure data are unchanged relative to an earlier time.

3. The system as defined in claim 1 wherein said means for sensing comprises a plurality of individual sensors.

4. The system as defined in claim 1 wherein said means for removing serial correlation comprises at least one of (1) means for Fourier filtering the raw data information, (2) means for performing autoregressive filtering of the raw data information or (3) means for passing the raw data information without filtering.

5. The system as defined in claim 4 wherein said means for Fourier filtering comprises a fast Fourier transformation software package.

6. The system as defined in claim 4 wherein low frequency components are filtered by the means for Fourier filtering and the high frequency components are removed by the means for performing autoregressive filtering.
7. The system as defined in claim 1 wherein said means for applying a probability ratio test further comprises means for performing a sequential probability ratio test.

8. The system as defined in claim 1 wherein said means for calculating Mahalanobis distribution data includes means for calculating Mahalanobis distributions for a plurality of combinations in which each one of said means for sensing is masked stepwise.

9. The system as defined in claim 8 wherein the Mahalanobis distribution data are recalculated at later times by the means for calculating Mahalanobis data, thereby ensuring no significant time drift of the raw data information output from the means for sensing.

10. The system as defined in claim 1 wherein said means for removing serial correlation comprises means for superpositioning and manipulating the raw data information and derivatives thereof characteristic of one of Fourier filtered data and autoregressively filtered data.

11. The system as defined in claim 10 wherein the means for removing serial correlation by autoregression includes means for skipping selected ones of the raw data information.

12. The system as defined in claim 10 wherein the means for removing serial correlation by autoregression includes recalculation means for comparing newly calculated filtered data with previously calculated filtered data.

13. The system as defined in claim 1 wherein said means for calculating Mahalanobis distribution data includes means for transforming principal components.

14. The system as defined in claim 1 wherein the means for applying a probability ratio test includes means for specifying an offset for the Mahalanobis distribution data characteristic of abnormal operation of the industrial process.

15. The system as defined in claim 1 wherein the probability ratio test comprises forming a ratio:

$$P_n = \frac{\text{probability of Mahalanobis distance sequence for no abnormality}}{\text{probability of Mahalanobis distance sequence for abnormality}} \tag{14}$$

where if $P_n > B$ implies no abnormality and if $P_n < A$ implies abnormality where A and B are assigned values for the particular said industrial process.

16. The system as defined in claim 15 wherein said system includes means for identifying a faulty one of said means for sensing, said means for identifying comprising means for masking sequentially each of said means for sensing and comparing the Mahalanobis distribution data, thereby obtaining P_n <A when the faulty one of said means for sensing is unmasked.

17. The system as defined in claim 16 wherein said means for identifying further includes means for masking sequentially more than one of said means for sensing, thereby enabling identification of more than one faulty one of said means for sensing.

18. A method for performing surveillance of an industrial process using industrial sensors to assess at least one of an operational state of the industrial process and viability of the sensors, comprising the steps of:

    sensing raw data information from the industrial process using a plurality of sensors;

    converting the raw data information to computer data and outputting the computer data to a computer;

    generating analyzable sensor data for the computer;

    executing computer software using the computer to remove serial correlation information present for each sensor alone between the raw data information accumulated by each of the sensors at different times;

    accumulating training data for the industrial process and the sensors characteristic of raw data information known to be representative of a properly functioning sensor and industrial process;

    further executing the computer software to calculate a statistical deviation from the training data by determining Mahalanobis distribution data for both the raw data information and the training data; and

    applying a probability ratio test to determine alarm conditions for abnormal states of the industrial process and the sensors.

19. The method as defined in claim 18 wherein the steps of removing serial correlation information comprises performing at least one of the step of Fourier filtering and autoregressively filtering the raw data information.

20. The method as defined in claim 18 further including the steps of performing a sequential probability ratio test after applying a probability ratio test of the Mahalanobis distribution data.

21. The method as defined in claim 18 wherein the step of determining the Mahalanobis distribution data includes sequentially calculating distribution data for multiple situations in which each one of said sensors is masked sequentially.

22. The method as defined in claim 18 wherein the Mahalanobis distribution data is recalculated periodically to ensure continuity with previous calculations.

23. The method as defined in claim 18 wherein the industrial process is selected from the group consisting of a nuclear power plant process, a fossil power plant process, an operating automobile, an operating aircraft, an operating ship, a water and waste treatment process, a pumping station process, an operating petroleum fluid pipeline, a chemical plant process and a biomedical process.

24. The method as defined in claim 18 wherein said step of executing computer software includes segmenting the raw data information into linear segments thereby characterizing nonlinear variable behavior as a plurality of segments of linear behavior.

25. The method as defined in claim 18 wherein the step of executing computer software includes the step of time averaging over slowly changing portions of the raw data information.

26. The method as defined in claim 18 wherein the step of executing computer software includes skipping analysis of selected portions of the raw data information over slowly changing portions of the raw data information.

27. The method as defined in claim 18 further including the step of generating an alarm for at least one of an automated response by a device operating the industrial process or a manual response by an operator.

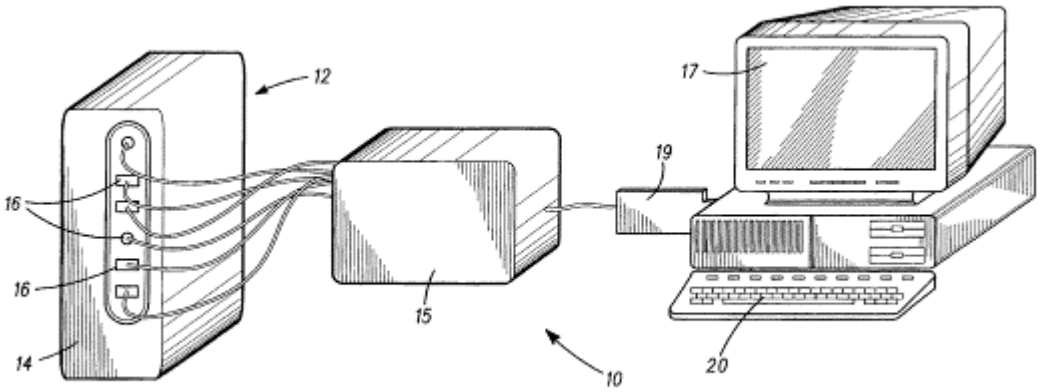

Fig. 1

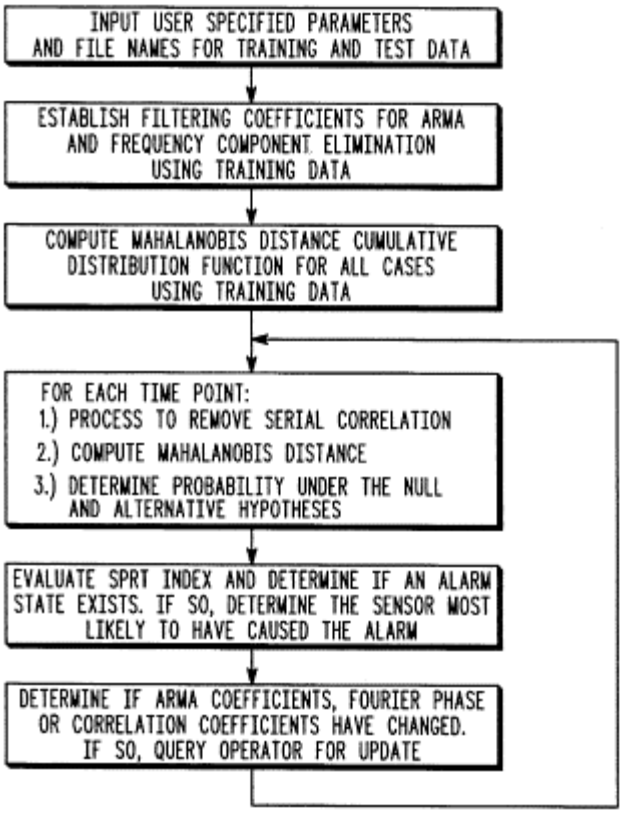
INPUT USER SPECIFIED PARAMETERS AND FILE NAMES FOR TRAINING AND TEST DATA
ESTABLISH FILTERING COEFFICIENTS FOR ARMA AND FREQUENCY COMPONENT ELIMINATION USING TRAINING DATA
COMPUTE MAHALANOBIS DISTANCE CUMULATIVE DISTRIBUTION FUNCTION FOR ALL CASES USING TRAINING DATA
FOR EACH TIME POINT:
1.) PROCESS TO REMOVE SERIAL CORRELATION
2.) COMPUTE MAHALANOBIS DISTANCE
3.) DETERMINE PROBABILITY UNDER THE NULL AND ALTERNATIVE HYPOTHESES
EVALUATE SPRT INDEX AND DETERMINE IF AN ALARM STATE EXISTS. IF SO, DETERMINE THE SENSOR MOST LIKELY TO HAVE CAUSED THE ALARM
DETERMINE IF ARMA COEFFICIENTS, FOURIER PHASE OR CORRELATION COEFFICIENTS HAVE CHANGED. IF SO, QUERY OPERATOR FOR UPDATE

Fig. 2

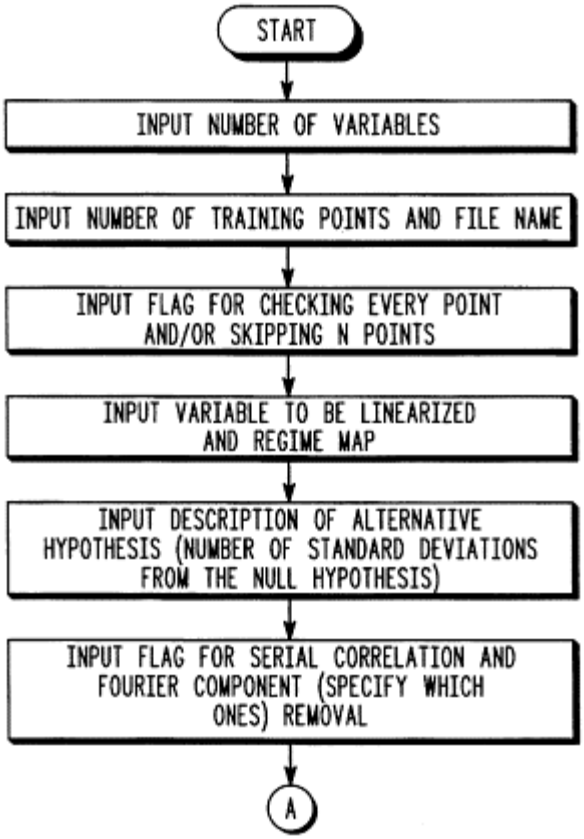
START
INPUT NUMBER OF VARIABLES
INPUT NUMBER OF TRAINING POINTS AND FILE NAME
INPUT FLAG FOR CHECKING EVERY POINT AND/OR SKIPPING N POINTS
INPUT VARIABLE TO BE LINEARIZED AND REGIME MAP
INPUT DESCRIPTION OF ALTERNATIVE HYPOTHESIS (NUMBER OF STANDARD DEVIATIONS FROM THE NULL HYPOTHESIS)
INPUT FLAG FOR SERIAL CORRELATION AND FOURIER COMPONENT (SPECIFY WHICH ONES) REMOVAL
A

Fig. 3A

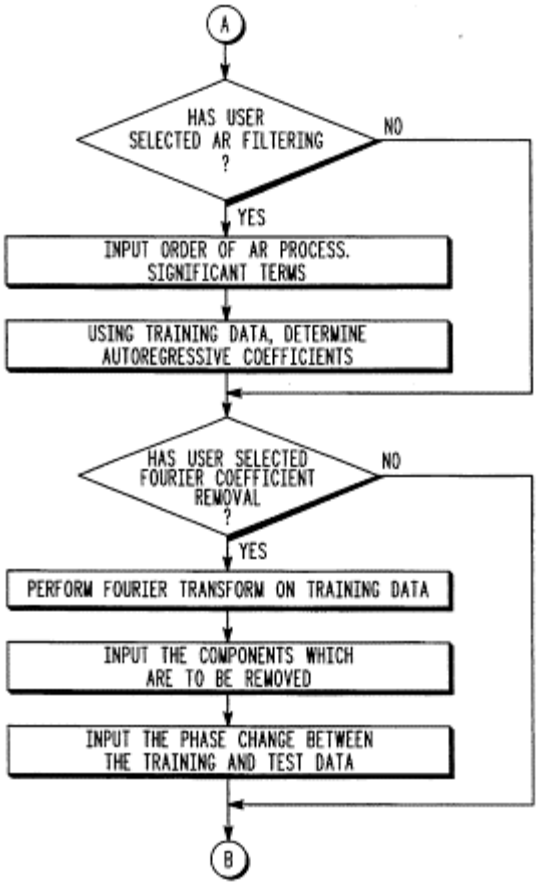
A
HAS USER SELECTED AR FILTERING ?
NO
YES
INPUT ORDER OF AR PROCESS. SIGNIFICANT TERMS
USING TRAINING DATA, DETERMINE AUTOREGRESSIVE COEFFICIENTS
HAS USER SELECTED FOURIER COEFFICIENT REMOVAL ?
NO
YES
PERFORM FOURIER TRANSFORM ON TRAINING DATA
INPUT THE COMPONENTS WHICH ARE TO BE REMOVED
INPUT THE PHASE CHANGE BETWEEN THE TRAINING AND TEST DATA
B

Fig. 3B

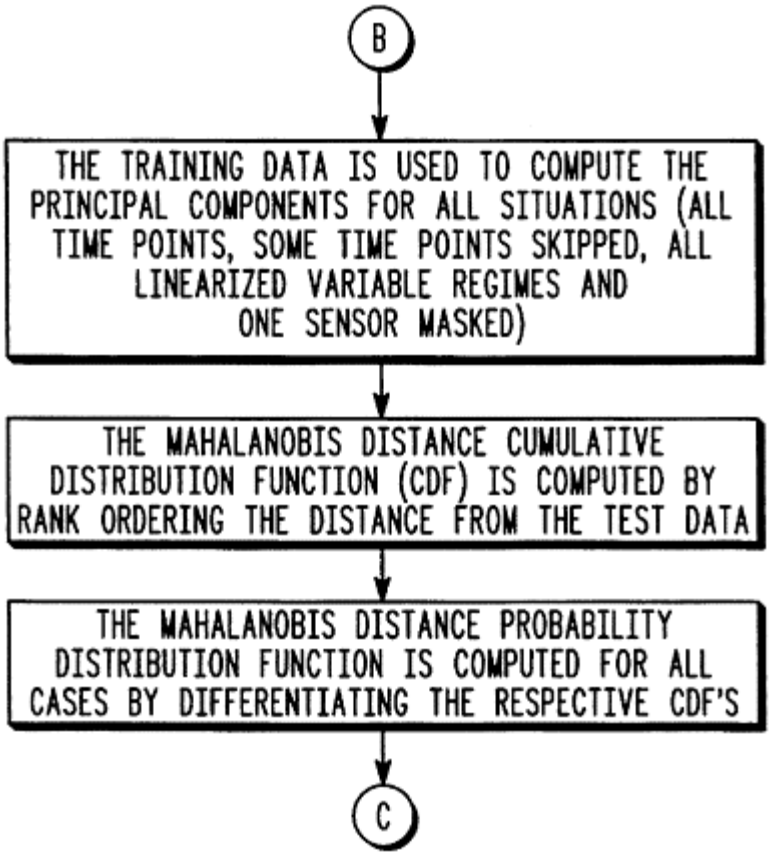
B
THE TRAINING DATA IS USED TO COMPUTE THE PRINCIPAL COMPONENTS FOR ALL SITUATIONS (ALL TIME POINTS, SOME TIME POINTS SKIPPED, ALL LINEARIZED VARIABLE REGIMES AND ONE SENSOR MASKED)
THE MAHALANOBIS DISTANCE CUMULATIVE DISTRIBUTION FUNCTION (CDF) IS COMPUTED BY RANK ORDERING THE DISTANCE FROM THE TEST DATA
THE MAHALANOBIS DISTANCE PROBABILITY DISTRIBUTION FUNCTION IS COMPUTED FOR ALL CASES BY DIFFERENTIATING THE RESPECTIVE CDF'S
C

Fig. 3C

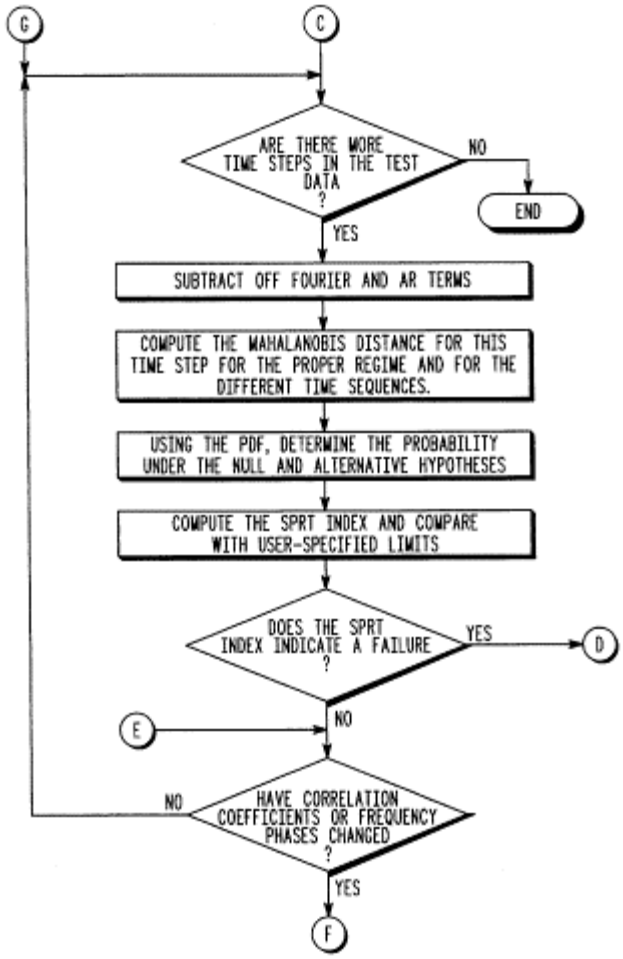
G
C
ARE THERE MORE TIME STEPS IN THE TEST DATA ?
NO
END
YES
SUBTRACT OFF FOURIER AND AR TERMS
COMPUTE THE MAHALANOBIS DISTANCE FOR THIS TIME STEP FOR THE PROPER REGIME AND FOR THE DIFFERENT TIME SEQUENCES.
USING THE PDF, DETERMINE THE PROBABILITY UNDER THE NULL AND ALTERNATIVE HYPOTHESES
COMPUTE THE SPRT INDEX AND COMPARE WITH USER-SPECIFIED LIMITS
DOES THE SPRT INDEX INDICATE A FAILURE ?
YES
D
E
NO
HAVE CORRELATION COEFFICIENTS OR FREQUENCY PHASES CHANGED ?
NO
YES
F

Fig. 3D

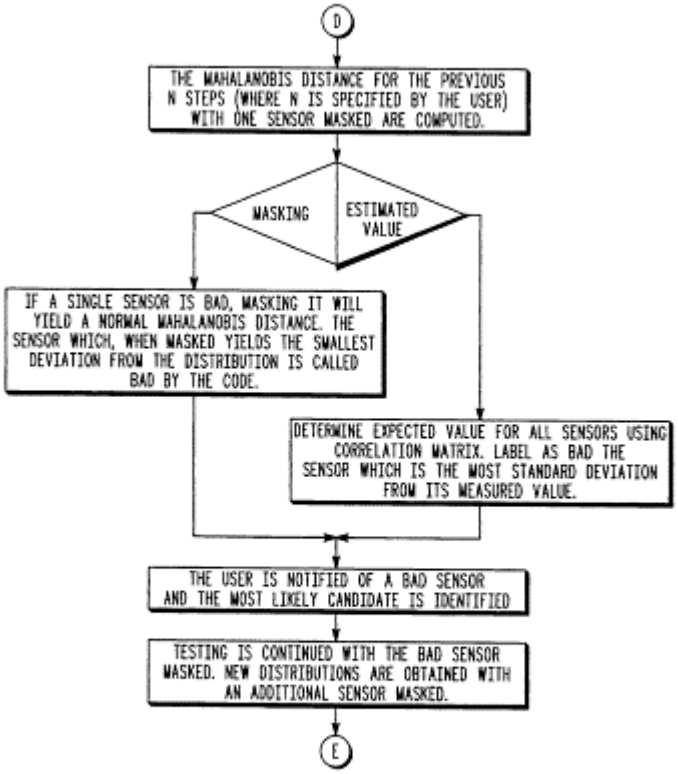
D
THE MAHALANOBIS DISTANCE FOR THE PREVIOUS N STEPS (WHERE N IS SPECIFIED BY THE USER) WITH ONE SENSOR MASKED ARE COMPUTED.
MASKING
ESTIMATED VALUE
IF A SINGLE SENSOR IS BAD, MASKING IT WILL YIELD A NORMAL MAHALANOBIS DISTANCE. THE SENSOR WHICH, WHEN MASKED YIELDS THE SMALLEST DEVIATION FROM THE DISTRIBUTION IS CALLED BAD BY THE CODE.
DETERMINE EXPECTED VALUE FOR ALL SENSORS USING CORRELATION MATRIX. LABEL AS BAD THE SENSOR WHICH IS THE MOST STANDARD DEVIATION FROM ITS MEASURED VALUE.
THE USER IS NOTIFIED OF A BAD SENSOR AND THE MOST LIKELY CANDIDATE IS IDENTIFIED
TESTING IS CONTINUED WITH THE BAD SENSOR MASKED. NEW DISTRIBUTIONS ARE OBTAINED WITH AN ADDITIONAL SENSOR MASKED.
E

Fig. 3E

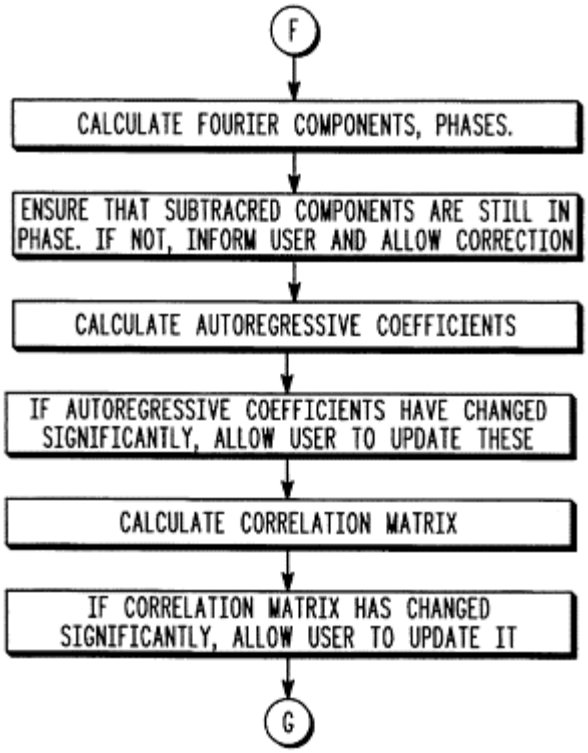
F
CALCULATE FOURIER COMPONENTS, PHASES.
ENSURE THAT SUBTRACRED COMPONENTS ARE STILL IN PHASE. IF NOT, INFORM USER AND ALLOW CORRECTION
CALCULATE AUTOREGRESSIVE COEFFICIENTS
IF AUTOREGRESSIVE COEFFICIENTS HAVE CHANGED SIGNIFICANTLY, ALLOW USER TO UPDATE THESE
CALCULATE CORRELATION MATRIX
IF CORRELATION MATRIX HAS CHANGED SIGNIFICANTLY, ALLOW USER TO UPDATE IT
G

Fig. 3G

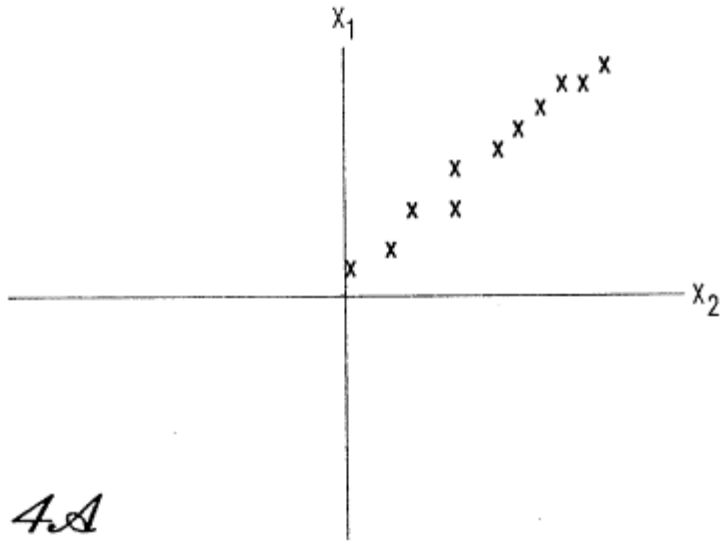

Fig. 4A

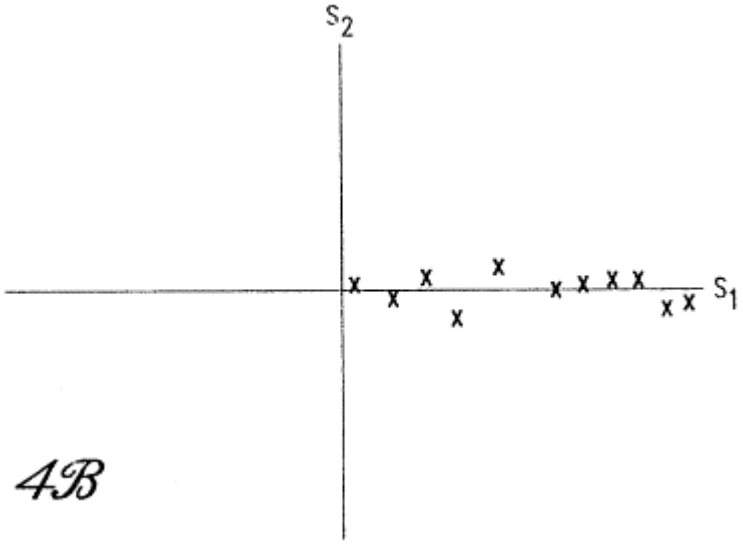

Fig. 4B