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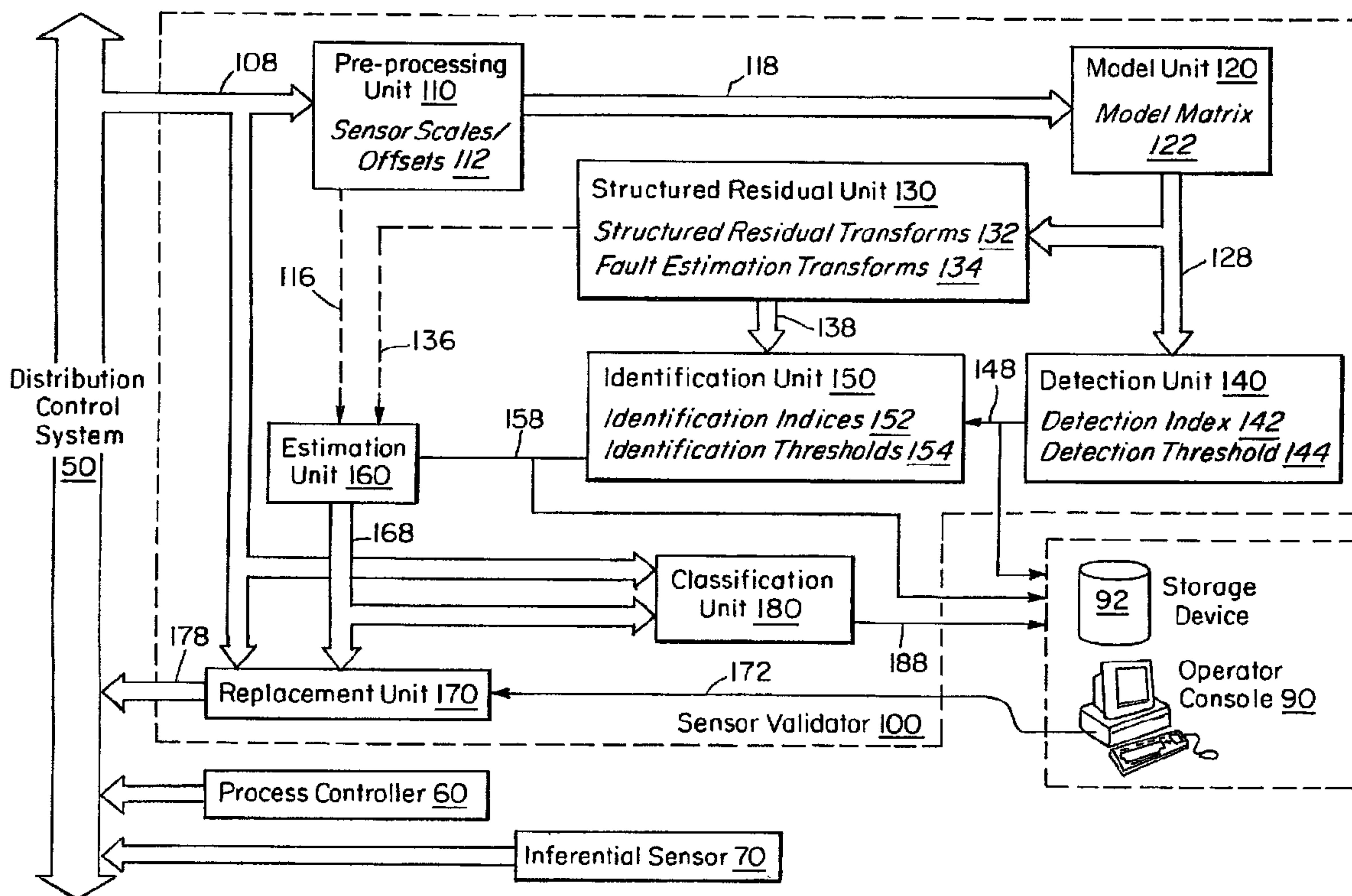
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## (54) Titre : PROCEDE ET DISPOSITIF DE VALIDATION DE CAPTEUR

(54) Title: SENSOR VALIDATION APPARATUS AND METHOD



(57) Abrégé/Abstract:

An apparatus and method is disclosed for detecting, identifying, and classifying faults occurring in sensors measuring a process. If faults are identified in one or more sensors, the apparatus and method provide replacement values for the faulty sensors so that any process controllers and process monitoring systems that use these sensors can remain in operation during the fault period. The identification of faulty sensors is achieved through the use of a set of structured residual transforms that are uniquely designed to be insensitive to specific subsets of sensors, while being maximally sensitive to sensors not in the subset. Identified faults are classified into one of the types Complete Failure, Bias, Drift, Precision Loss, or Unknown.

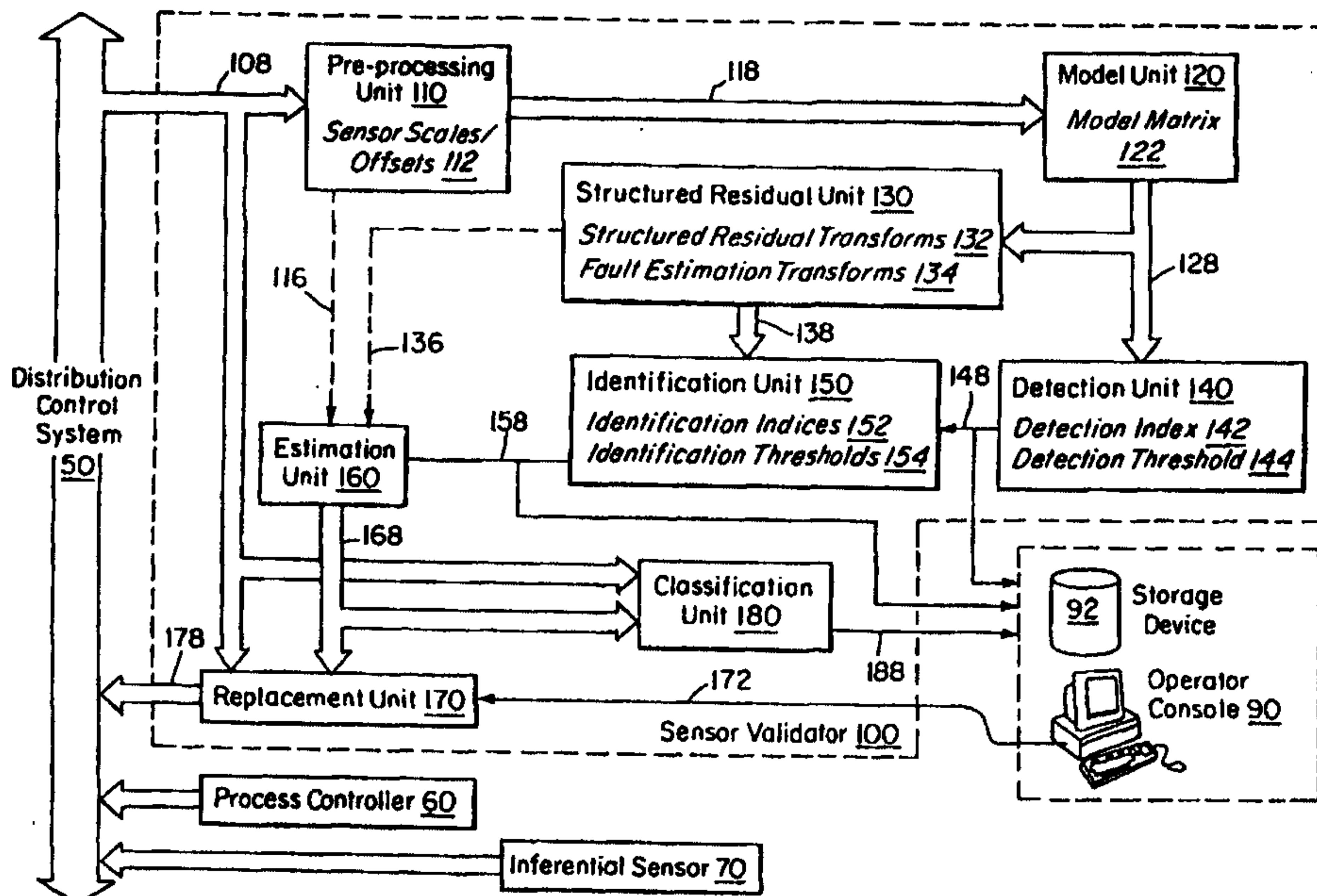
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(54) Title: SENSOR VALIDATION APPARATUS AND METHOD



### (57) Abstract

An apparatus and method is disclosed for detecting, identifying, and classifying faults occurring in sensors measuring a process. If faults are identified in one or more sensors, the apparatus and method provide replacement values for the faulty sensors so that any process controllers and process monitoring systems that use these sensors can remain in operation during the fault period. The identification of faulty sensors is achieved through the use of a set of structured residual transforms that are uniquely designed to be insensitive to specific subsets of sensors, while being maximally sensitive to sensors not in the subset. Identified faults are classified into one of the types *Complete Failure, Bias, Drift, Precision Loss, or Unknown*.

## SENSOR VALIDATION APPARATUS AND METHOD

## I. Field of the Invention

5                   The present invention pertains, in general, to process controllers and process monitoring systems that make use of sensors for measuring process variables. In particular it relates to a system that detects and identifies one or more sensor faults, classifies the types 10 of sensor fault, and replaces erroneous sensor values with estimates of the correct process variable values.

## II. Background of the Invention

15                  Sensor validation is an important step for many model based applications in the process industries. Typical model based applications include model predictive control applications (MPC), and inferential sensing applications in which costly or infrequent measurements, available from 20 laboratory samples or hardware analyzers, are replaced by regularly available inferred values from the model.

25                  Sensor validation systems exist. A system for determining DC drift and noise level using parity-space validation is described in United States Patent No. 4,772,445 by Nasrallah et al. The system measures direct current drift and noise in sensor signals from redundant sensors utilizing a parity-space algorithm. Parity vector signals produced by the parity-space algorithm are averaged to provide a direct current (DC) drift signal. An instantaneous noise signal is found by subtracting the 30 direct current drift signal from a parity vector signal for one of the samples of the sensor signals. The RMS value of the instantaneous noise signals are averaged to provide sensors noise signals.

35                  In a typical MPC application, steady state optimization is performed to find the optimal target values for the controlled and manipulated variables. If the sensors are

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faulty, the optimized target values are not valid. Therefore, an effective sensor validation approach that detects and identifies faulty sensors on-line is required. Once a faulty sensor is identified, it is desirable to

5 estimate the fault magnitude and replace

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it with the best reconstruction in order to maintain the control system on-line even though a sensor has failed.

A typical inferential sensor application is in the area of predictive emissions monitoring systems (PEMS). Federal and/or state regulations may require air-polluting plants to monitor their emissions such as nitrogen oxides ( $\text{NO}_x$ ), oxygen ( $\text{O}_2$ ), and carbon monoxide (CO). Hardware continuous emissions monitoring systems (CEMS) have both a high initial cost and a high maintenance cost. CEMS can be replaced by PEMS provided the PEMS is shown to be sufficiently accurate and reliable. One of the quality assurance requirements for PEMS is that each sensor that is used in the PEMS model be monitored for failure, and have a strategy for dealing with sensor failure so as to minimize down-time.

The term sensor validation refers, for this patent application, to multivariate model based sensor validation. This is an approach which makes use of redundancy in the plant measurements. Typically sensor measurements exhibit a correlation structure which can be established by a training procedure using collected or historian data. This correlation structure can be monitored online; when the correlation structure is broken a possible sensor fault has occurred. However the breaking of this correlation structure could also be due to process upset, process transition, or some other reason unrelated to sensor fault. The main objective is to determine if this really is a sensor fault and, if so, to identify the offending sensor. The various phases of sensor validation can be summarized as:

- Detection This phase detects a change in the correlation structure; it may or may not be a sensor fault.
- 25 • Identification This phase determines if this is a sensor fault and identifies the particular sensor
- Estimation This phase estimates the size of the fault which allows reconstruction of the true value and replacement of the faulty value

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- Classification This phase classifies the type of sensor fault – complete failure, bias, drift, or precision loss

Depending on the particular approach, these phases may overlap. There have been several patents granted that address the topic of multivariate model based sensor validation. The key ones are:

- Qin et al. US patent 5,680,409 "Method and Apparatus for detecting and identifying faulty sensors in a process"
- Keeler et al. US patent 5,548,528 "Virtual Continuous Emission Monitoring System"
- 10 • Hopkins et al. US patent 5,442,562 "Method of controlling a manufacturing process using multivariate analysis"

Qin et al. address sensor validation within the context of process control. The preferred embodiment is based on PCA (Principal Components Analysis) and performs identification through an optimal reconstruction procedure: each sensor 15 value is reconstructed on the assumption it is at fault, then identification and classification is done by tracking indices derived from the reconstruction error.

Keeler et al. address sensor validation explicitly within the context of PEMS. The disclosed system focuses on the inferential sensor technology and the use of neural networks for PEMS. The sensor validation technology uses a sub-optimal 20 reconstruction procedure for identification, does not address classification, and makes use of an "encoder" neural network which is a non-linear version of PCA. Encoder networks are also described in Mark Kramer "Nonlinear principal component analysis using autoassociative neural networks", *AIChe Journal*, 37 (2), pp. 233-243 (1991).

Hopkins et al. address sensor validation within the context of process monitoring 25 (multivariate statistical process control), and make use of PCA or PLS (Partial Least Squares). Identification is by means of contribution analysis. Detection is achieved by monitoring principal component "scores" or score statistics and comparing with standard confidence intervals. Identification is by examining the contributions of each

original measurement to the offending score. The method does not attempt to classify fault types.

### III SUMMARY OF THE INVENTION

The present invention provides a new apparatus and method for the detection, 5 identification, estimation, reconstruction, and classification of faulty sensors. The approach makes use of a normal process model that can be built from first principles or from data using statistical methods such as partial least squares (PLS) or principal component analysis. In the preferred embodiment, the process model is based on a PCA model in which the number of principal components is chosen to optimize the 10 reconstruction of faulty sensor values as described in Qin and Dunia "Determining the number of principal components for best reconstruction", *Proc. of the 5-th IFAC Symposium on Dynamics and Control of Process Systems*, 359-364, Corfu, Greece, June 8-10, 1998.

The detection phase uses a detection index based on the model *equation error*. An 15 exponentially weighted moving average (EWMA) filter is applied to the detection index to reduce false alarms due to temporary transients. The filtered detection index (*FDI*) is compared to a statistically derived threshold in order to detect possible faults. Detection of a possible fault condition triggers the identification phase of the invention.

20 The key component of this invention is the identification phase. To determine whether a detection alarm is due to one or more faulty sensors, and to identify the offending sensor(s), a series of detectors are constructed which are insensitive to one subset of faults but most sensitive to the others. These detectors are based on *structured residuals (SRs)* constructed by means of a novel approach referred to a 25 *structured residual approach with maximized sensitivity (SRAMS)*. Structured residuals are generally described in Gertler and Singer, "A new structural framework for parity equation based failure detection and isolation", *Automatica* 26:381-388, 1990. An exponentially weighted moving average (EWMA) filter is applied to the SRs to reduce false alarms due to temporary transients. The SRs are also squared and 30 normalized so as to equitably compare different SRs. Identification is achieved by comparing these normalized squared filtered structured residuals (*NSFSRs*) to

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statistically inferred confidence limits. In addition to *NSFSRs*, indices based on the accumulation of the normalized structured residuals (*NSRs*) from the time of detection are monitored and compared for use in the identification of  
5 faulty sensors. Two such indices are the generalized likelihood ratio (*GLR*) index, and the normalized cumulative variance (*NCUMVAR*) index. The *NCUMVAR* index is primarily useful for identifying sensors with precision degradation.

10 The fault magnitude is then optimally estimated based on the model, faulty data, and the assumption that the faulty sensors have been correctly identified. This uses public domain prior art described, for example, Martens and Naes "Multivariate Calibration", *John Wiley and Sons, New York*,  
15 1989. Knowledge of the fault direction (known from the identification of the faulty sensors) and the estimated fault magnitude is then used to reconstruct estimates of the correct sensor values.

20 The fault classification phase provides diagnostic information as to the type of sensor fault. Specifically, four types of fault are considered: *Complete Failure*, *Bias*, *Drift*, and *Precision Loss*. *Complete failure* is determined by performing a regression analysis on an identified faulty  
25 sensor's measured values, and is indicated by the statistical inference that the regression line has zero slope. The other three types of fault are classified by performing a regression analysis on the estimated fault sizes since the time of identification. *Bias* is indicated by the statistical inference that the estimated fault size regression line has zero slope and non-zero offset, and has small residual error. *Drift* is indicated by the statistical inference that the estimated fault size regression line has non-zero slope, and has small residual error. *Precision Loss*

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is indicated by the statistical inference that estimated fault size regression line has zero slope, zero offset, and significant residual error. *Precision Loss* is also indicated if the fault is identifiable only by the *NCUMVAR* index.

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According to one aspect of the present invention there is provided an apparatus for detecting one or more sensor faults in a measured process, wherein the improvement comprises: a per-processing unit for receiving a working vector of signals including measured sensor values, the pre-processing unit having means for normalizing the measured sensor values, resulting in pre-processed sensor values; a model unit coupled to the pre-processing unit, which converts pre-processed sensor values to equation error values that contain mainly measurement noise; a structured residual unit coupled to the model unit, which contains a plurality of transforms, referred to as structured residual transforms, each such transform converting equation error values to a structured residual value, and each such transform is optimally designed to be insensitive to faults in a subset of sensors; a detection unit coupled to the model unit, the detection unit monitoring the relationship among the equation error values, occurrence of a significant deviation of said relationship from expected relationship resulting in a detection event; an identification unit coupled to the structured residual unit and the detection unit, the identification unit being activated by a detection event, and using the structured residual values to determine if one or more sensors are faulty, said determination resulting in an identification event; an estimation unit coupled to the pre-processing unit, the structured residual unit and the identification unit, the estimation unit being activated by an identification event, and estimating fault sizes for each of the identified faulty sensors; a replacement unit coupled to the estimation unit, the replacement unit calculating replacement values for the faulty measured sensor values in the working signal values

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by subtracting the estimated fault size from the corresponding measured sensor value for all identified faults; and a classification unit coupled to the estimation unit, the classification unit being active when the estimation unit is active, and classifying the identified sensor faults into a fixed set of fault types.

According to a further aspect of the present invention there is provided a computer method for detecting one or more sensor faults in a measured process wherein the improvement comprises the steps of: receiving a working vector of signals including measured sensor values, and preprocessing the measured sensor values, resulting in pre-processed sensor values; converting the pre-processed sensor values to equation error values that contain mainly measurement noise; applying a plurality of transforms to the equation error values resulting in a plurality of structured residual values, said transforms referred to as structured residual transforms and optimally designed to be insensitive to faults in a subset of sensors; monitoring a relationship among the equation error values, an occurrence of a significant deviation of said relationship from expected relationship resulting in a detection event; in the case that a detection event occurs, using the structured residual values to determine if one or more sensors are faulty, said determination resulting in an identification event; in the case that an identification event occurs, estimating fault sizes for each of the identified faulty sensors; in the case that an identification event occurs, replacing faulty measured sensor values in the working signal with corrected values by subtracting the estimated fault size from the corresponding measured sensor value for all identified faults; and in the case that an identification event occurs, classifying the identified sensor faults into a fixed set of fault types.

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#### IV BRIEF DESCRIPTION OF THE DRAWINGS

The foregoing and other objects, features, and  
5 advantages of the invention will be apparent from the  
following more particular description of preferred  
embodiments of the invention, as illustrated in the  
accompanying drawings in which like reference characters  
refer to the same parts throughout the different views. The  
10 drawings are not

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necessarily to scale, emphasis instead being placed upon illustrating the principles of the invention.

*FIG. 1* shows the eight computational units of the preferred embodiment of the invention and the relationships between these units.

5 *FIG. 2* shows a flow diagram of the identification process in the embodiment of *FIG. 1*.

*FIG. 3* shows a flow diagram of the classification process in the embodiment of *FIG. 1*.

10 *FIG. 4* shows the detection index of the present invention rapidly increasing and exceeding its threshold on the introduction of a fault to a boiler process.

*FIG. 5* shows the output of the *Estimation Unit* on introduction of a bias fault into sensor 2 of a boiler process.

*FIG. 6* shows the output of the *Estimation Unit* on introduction of a drift fault into sensor 5 of a boiler process.

15 *FIG. 7* shows the *NSFSR* indices of the present invention in response to the introduction of a drift fault into sensor 5 of a boiler process.

## V DETAILED DESCRIPTION OF THE PREFERRED EMBODIMENTS

The sensor validation apparatus 100 of this invention is shown in *FIG. 1*. The external input to the sensor validator consists of sensor measurements 108, which may 20 include status information, as might be available, for example, from a Distributed Control System (DCS) 50 in a manufacturing plant. The purpose of the invention is to use redundant information in the sensor measurements to detect when a sensor has failed, and, optionally, to provide a replacement value for a failed sensor. Other devices such as a process controller 60 or inferential sensor 70 that make use of the 25 sensor measurements can then use the replacement values if necessary. This allows these devices to continue operation in the presence of failed sensors.

Referring again to *FIG. 1*, the sensor validator 100 consists of eight computational units that implement the various phases of sensor validation. These

computational units, which may be implemented using a microprocessor or any other desired type of computer, are as follows:

- A *Pre-processing Unit 110*, which maintains scaling and offset information 112 to convert the vector of sensor values 108 from the DCS 50 to a vector of normalized values 118. These normalized values have standardized units for which, in the preferred embodiment, the values are designed to have a mean of 0 and a standard deviation of 1. This is necessary for building an effective model matrix 122, detection index 142, and structured residual transforms 132 for identifying faulty sensors. The scaling and offset information is, in the preferred embodiment, 5 derived from a statistical analysis of a historical set of sensor data.
- A *Model Unit 120*, which maintains a model matrix 122 to convert the vector of pre-processed sensor values 118 at a given instance to an error vector referred to as the equation error 128. The equation error is used by the *Structured Residual Unit 130* to calculate structured residuals values 138 and fault sizes 136, and by 10 the *Detection Unit 140* to calculate the detection index 142. The *Structured Residual Unit* also uses the model matrix to design structured residual transforms 132 and their corresponding fault estimation transforms 134. The model matrix is, 15 in the preferred embodiment, built from a historical set of sensor data using Principal Component Analysis.
- A *Structured Residual Unit 130*, which maintains a working set of structured residual transforms 132 that convert the current equation error 128 to a set of structured residual values 138. The *Identification Unit 150* uses these structured residual values to determine the identity of any faulty sensors. The *Structured Residual Unit* also maintains a set of fault estimation transforms 134 that are used 20 by the *Estimation Unit 160* to obtain normalized fault sizes 136 for identified faults.
- A *Detection Unit 140*, which calculates a detection index 142 from the equation error 128, and compares the detection index to detection threshold 144. If the detection index exceeds the detection threshold, then a detection event 148 is 25 generated. This detection event is used to activate the *Identification Unit 150*, and 30

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is also available externally to the sensor validator, for example for operator alarm generation or event logging to an operator console 90, or to a storage device 92.

- An *Identification Unit* 150, which uses the structured residual values 138 to calculate several sets of identification indices 152. If a detection event 148 has occurred, then the *Identification Unit* attempts to identify the nature of the fault by comparing the identification indices to a corresponding set of thresholds 154, according to a certain logic, described in detail later. If identification is successful, an identification event 158 is generated which is used to activate the *Estimation Unit*. This identification event includes information as to which sensors failed, and is also available externally to the sensor validator, for example for operator alarm generation or event logging to an operator console 90, or to a storage device 92.
- An *Estimation Unit* 160, which is activated by an identification event 158. The *Estimation Unit* requests the *Structured Residual Unit* 130 to apply the appropriate fault estimation transform 134 (chosen based on identification information) to the equation error 128, resulting in normalized fault size information 136. The *Estimation Unit* then applies the appropriate scaling 116 to 136, in order to produce fault size estimates 168 scaled to the units of the original sensor values.
- A *Replacement Unit* 170, which subtracts the estimated fault sizes 168 from the corresponding faulty sensor measurements 108, to obtain a set of replacement values 178. These replacement values are available externally to the sensor validator; for example they are written to the DCS 50 for use by other devices. The *Replacement Unit* is only active when the *Estimation Unit* 160 is active. It can also be deactivated by request of an operator 172; in this case the output 178 of the *Replacement Unit* is identical to the original input 108 to the sensor validator.
- A *Classification Unit* 180, which calculates diagnostic information as to the type of sensor fault. Specifically, four types of fault are considered: *Complete Failure*, *Bias*, *Drift*, and *Precision Loss*. The *Classification Unit* is only active when the *Estimation Unit* 160 is active, which, in turn, is only active when an identification event 158 has been generated. The classification is based on an analysis of the sensor data 108 and the fault size estimations 168 since the time of identification. The classification information 188 produced by the *Classification Unit* is available

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externally to the sensor validator, for example for operator alarm generation or event logging to an operator console 90, or to a storage device 92.

A detailed description of the preferred embodiment of each of these computational units now follows.

## 5 V.1 PRE-PROCESSING UNIT

The *Pre-processing Unit 110* calculates and maintains scaling and offset information to convert between measured sensor values 108 from the DCS and normalized values 118 for inputting to the *Model Unit* and the *Structured Residual Unit*. The scale value  $s_i$  and offset value  $o_i$  for the  $i^{th}$  sensor are, in the preferred embodiment of this invention, calculated from the mean  $\mu_i$  and standard deviation  $\sigma_i$  of the  $i^{th}$  sensor as follows:

$$s_i = \frac{1}{\sigma_i} \quad (1)$$

$$o_i = \mu_i$$

Then a measured value  $u_i$  of the  $i^{th}$  sensor is converted to a normalized value  $x_i$  by:

$$15 \quad u_i = s_i(x_i - o_i) \quad (2)$$

$\mu_i$  and  $\sigma_i$  are estimated from representative sample data in the standard way well known to those skilled in the art.

## V.2 MODEL UNIT

The *Model Unit 120* maintains a normal process model, which can be represented by the following equation:

$$Bx^*(t) = e^*(t) \quad (3)$$

where  $x^* \in \mathbb{R}^n$  is a vector of preprocessed sensor values,  $B \in \mathbb{R}^{m \times n}$  is the model matrix 122, and  $e^* \in \mathbb{R}^m$  is the equation error 128. The matrix  $B$  can be derived from mass balance or energy balance of the process, or it can be generated from process

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data using statistical methods such as Principal Component Analysis (PCA) or Partial Least Squares (PLS).

#### V.2.1 MODEL UNIT BASED ON PCA

5 In the preferred embodiment, the normal process model is derived from process data using PCA. PCA is generally described in, for example, J. Edward Jackson "A User's Guide to Principal Components" *John Wiley* 1991. In PCA the sensor values  $\mathbf{x}^*(t) \in \mathbb{R}^n$  are decomposed into:

$$\mathbf{x}^*(t) = \mathbf{P}\mathbf{P}^T\mathbf{x}^*(t) + \tilde{\mathbf{P}}\tilde{\mathbf{P}}^T\mathbf{x}^*(t) \quad (4)$$

10 where  $\mathbf{P} \in \mathbb{R}^{n \times (n-m)}$  are the eigenvectors associated with the principal eigenvalues  $\lambda_1 \geq \lambda_2 \geq \dots \geq \lambda_{n-m}$  of the correlation matrix of  $\mathbf{x}^*(t)$ . In this case, the model equation error  $\mathbf{e}^*(t)$  corresponds to the residual components  $(\lambda_{n-m+1}, \dots, \lambda_n)$ , and, as described in Gertler, Li, Huang and McAvoy "Isolation enhanced principal component analysis" *Proc. IFAC Workshop on On-line Fault Detection and Supervision in the Chemical Process Industries*, 4-5 June, 1998,

$$\mathbf{B} = \tilde{\mathbf{P}}^T \quad (5)$$

20 In the preferred embodiment, the optimal number of principal components is chosen for optimal reconstruction capability as described in detail in Qin and Dunia "Determining the number of principal components for best reconstruction", *Proc. of the 5-th IFAC Symposium on Dynamics and Control of Process Systems*, 359-364, Corfu, Greece, June 8-10, 1998.

#### V.3 STRUCTURED RESIDUAL UNIT

25 The *Structured Residual Unit 130* maintains transforms that are sensitive or insensitive to faults in certain directions. These transforms are described in the context of the following fault representation.

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### V.3.1 FAULT REPRESENTATION

Under normal conditions, the equation error  $\mathbf{e}^*(t)$  128 contains mainly measurement noise, which can be assumed to be zero mean Gaussian noise. When a sensor fault occurs, the sensor measurement will contain the normal values of the process variables and the fault, i.e.,

$$\mathbf{x}(t) = \mathbf{x}^*(t) + \Xi_i \mathbf{f}_i(t) \quad (6)$$

where  $\mathbf{f}_i(t) \in \mathbb{R}^{l_i}$  is a vector of the fault magnitude, and  $\Xi_i \in \mathbb{R}^{n \times l_i}$  is a matrix of fault directions. To represent a single sensor fault in the  $i^{th}$  sensor

$$\Xi_i = [0 \ 0 \ \Lambda \ 1 \ \Lambda \ 0]^T \quad (7)$$

10 which is the  $i^{th}$  column of the identity matrix. To represent simultaneous multiple sensor faults,  $\Xi_i$  simply contains the corresponding columns of the identity matrix. Using the measurement relation of equation 6 that contains a sensor fault, the equation error 128 can be written as follows:

$$\mathbf{e}(t) = \mathbf{Bx}(t) = \mathbf{Bx}^*(t) + \mathbf{B}\Xi_i \mathbf{f}_i(t) = \mathbf{e}^*(t) + \mathbf{B}\Xi_i \mathbf{f}_i(t) \quad (8)$$

15 The fault will in general cause the equation error  $\mathbf{e}(t)$  to increase. The magnitude of the equation error is used to detect sensor faults as described later. Since a distinct vector or matrix  $\Xi_i$  represents each sensor fault, fault identification can be accomplished by using the direction vectors.

### V.3.2 STRUCTURED RESIDUAL TRANSFORMATIONS FOR SINGLE FAULTS

20 The *Structured Residual Unit* 130 maintains a set of transforms referred to as structured residuals. The *Identification Unit* 150, described in a later section, uses the structured residual transforms to identify faulty sensors.

25 Structured residuals are generally described in Gertler and Singer, "A new structural framework for parity equation based failure detection and isolation", *Automatica* 26:381-388, 1990. In the present invention, a new design method for structured residuals is disclosed, referred to as "Structured Residual Approach with Maximized Sensitivity" or SRAMS.

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For the case of single sensor fault in the  $j^{th}$  sensor,

$$\mathbf{B}\Xi_j = \mathbf{b}_j \quad (9)$$

where  $\mathbf{b}_j$  is the  $j^{th}$  column of matrix  $\mathbf{B}$ . Therefore, the model equation error is

$$\mathbf{e}(t) = \mathbf{e}^*(t) + \mathbf{b}_j f_j(t) \quad (10)$$

5 With a selected residual structure, a set of structured residuals  $\mathbf{r}(t)$  can be generated by pre-multiplying the equation error vector  $\mathbf{e}(t)$  by a transformation matrix  $\mathbf{W}$ ,

$$\mathbf{r}(t) = \mathbf{W}\mathbf{e}(t) \quad (11)$$

It is desirable to design each element of  $\mathbf{r}(t)$  to be responsible for one particular sensor fault but not responsible for other faults. The  $i^{th}$  element of  $\mathbf{r}(t)$  given that the 10  $j^{th}$  sensor is faulty is represented as

$$r_{ij}(t) = \mathbf{w}_i^T \mathbf{e}(t) = \mathbf{w}_i^T \mathbf{e}^*(t) + \mathbf{w}_i^T \mathbf{b}_j f_j(t) \quad i, j = 1, 2, \dots, n \quad (12)$$

where  $\mathbf{w}_i^T$  is the  $i^{th}$  row of matrix  $\mathbf{W} \in \mathbb{R}^{n \times m}$ . Since  $\mathbf{e}(t)$  is random noise, one can only design the residual  $r_{ij}(t)$  to be sensitive or insensitive to  $\mathbf{b}_j$ , the fault direction vector. The SRAMS design criterion is stated as follows:

15 Choose  $\mathbf{w}_i$  such that  $r_{ij}(t)$  is insensitive to the  $i^{th}$  sensor fault but most sensitive to the others. Mathematically, this is equivalent to

$$\max_{\mathbf{w}_i} \sum_{j \neq i} \frac{(\mathbf{w}_i^T \mathbf{b}_j)^2}{\|\mathbf{w}_i\|^2 \|\mathbf{b}_j\|^2}$$

subject to:

$$\mathbf{w}_i^T \mathbf{b}_i = 0$$

20 Geometrically,  $\mathbf{w}_i$  is chosen to be orthogonal to  $\mathbf{b}_i$ , while minimizing its angle to other fault directions  $\mathbf{b}_j$ ,  $j \neq i$ . This problem can be equivalently stated as follows:

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$$\max_{\mathbf{w}_i} \sum_{j \neq i} (\mathbf{w}_i^T \mathbf{b}_j^o)^2 \quad (13)$$

subject to:

$$\begin{aligned} \mathbf{w}_i^T \mathbf{b}_i^o &= 0 \\ \|\mathbf{w}_i\| &= 1 \end{aligned}$$

where

$$5 \quad \mathbf{b}_j^o = \frac{\mathbf{b}_j}{\|\mathbf{b}_j\|} \quad j = 1, 2, \dots, n \quad (14)$$

To satisfy the constraint  $\mathbf{w}_i^T \mathbf{b}_i^o = 0$ , the vector  $\mathbf{w}_i$  must be chosen as follows:

$$\mathbf{w}_i = (\mathbf{I} - \mathbf{b}_i^o \mathbf{b}_i^{oT}) \mathbf{z}_i \in S_{\mathbf{w}_i}, \quad \mathbf{z}_i \in \mathbb{R}^m \quad (15)$$

where  $S_{\mathbf{w}_i}$  is the orthogonal complement of  $\mathbf{b}_i$ . Therefore, the solution of  $\mathbf{w}_i$  is converted to the solution of  $\mathbf{z}_i$ . Using a Lagrange multiplier  $\lambda$ , the solution of  $\mathbf{z}_i$  can 10 be found by maximizing the following objective:

$$\begin{aligned} J &= \max_{\mathbf{z}_i} \left( \sum_{j \neq i} (\mathbf{z}_i^T (\mathbf{I} - \mathbf{b}_i^o \mathbf{b}_i^{oT}) \mathbf{b}_j^o)^2 + \lambda (1 - \mathbf{z}_i^T (\mathbf{I} - \mathbf{b}_i^o \mathbf{b}_i^{oT}) \mathbf{z}_i) \right) \\ &= \max_{\mathbf{z}_i} \left( \sum_{j=1}^N (\mathbf{z}_i^T (\mathbf{I} - \mathbf{b}_i^o \mathbf{b}_i^{oT}) \mathbf{b}_j^o)^2 + \lambda (1 - \mathbf{z}_i^T (\mathbf{I} - \mathbf{b}_i^o \mathbf{b}_i^{oT}) \mathbf{z}_i) \right) \end{aligned} \quad (16)$$

The above relation holds because  $(\mathbf{I} - \mathbf{b}_i^o \mathbf{b}_i^{oT}) \mathbf{b}_i^o = 0$ . Denoting

$$[\mathbf{b}_1^o \quad \dots \quad \mathbf{b}_n^o] \equiv \mathbf{B}^o \quad (17)$$

and

$$15 \quad (\mathbf{I} - \mathbf{b}_i^o \mathbf{b}_i^{oT}) [\mathbf{b}_1^o \quad \dots \quad \mathbf{b}_n^o] = (\mathbf{I} - \mathbf{b}_i^o \mathbf{b}_i^{oT}) \mathbf{B}^o \equiv \mathbf{B}_i^o \quad (18)$$

which is the projection of  $\mathbf{B}^o$  onto  $S_{\mathbf{w}_i}$ , the maximization problem can be rearranged as follows:

$$J = \max_{\mathbf{z}_i} \left( \|\mathbf{B}_i^o \mathbf{z}_i\|^2 + \lambda (1 - \mathbf{z}_i^T (\mathbf{I} - \mathbf{b}_i^o \mathbf{b}_i^{oT}) \mathbf{z}_i) \right) \quad (19)$$

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Differentiating  $J$  with respect to  $\mathbf{z}_i$  leads to

$$\mathbf{B}_i^o \mathbf{B}_i^{oT} \mathbf{z}_i = \lambda \left( \mathbf{I} - \mathbf{b}_i^o \mathbf{b}_i^{oT} \right) \mathbf{z}_i \quad (20)$$

Note that

$$\begin{aligned} \mathbf{B}_i^o &= \left( \mathbf{I} - \mathbf{b}_i^o \mathbf{b}_i^{oT} \right) \mathbf{B}^o \\ &= \left( \mathbf{I} - \mathbf{b}_i^o \mathbf{b}_i^{oT} \right)^2 \mathbf{B}^o \\ &= \left( \mathbf{I} - \mathbf{b}_i^o \mathbf{b}_i^{oT} \right) \mathbf{B}_i^o \end{aligned} \quad (21)$$

5 Equation 20 can be rearranged as

$$\left( \mathbf{I} - \mathbf{b}_i^o \mathbf{b}_i^{oT} \right) \left( \mathbf{B}_i^o \mathbf{B}_i^{oT} \mathbf{z}_i - \lambda \mathbf{z}_i \right) = \mathbf{0}$$

or

$$\mathbf{B}_i^o \mathbf{B}_i^{oT} \mathbf{z}_i - \lambda \mathbf{z}_i = \mathbf{0} \quad (22)$$

Therefore  $\mathbf{z}_i$  is the eigenvector of  $\mathbf{B}_i^o \mathbf{B}_i^{oT}$  that corresponds to the largest eigenvalue.

10 After  $\mathbf{z}_i$  is known,  $\mathbf{w}_i$  can be easily calculated from equation 15.

### V.3.3 STRUCTURED RESIDUAL TRANSFORMATIONS FOR MULTIPLE FAULTS

The SRAMS design method can be extended to the case in which multiple sensors fail simultaneously. The equation error vector for multiple sensor faults is

$$\mathbf{e}(t) = \mathbf{e}^*(t) + \mathbf{b}_i \Xi_i \mathbf{f}_i(t) \quad (23)$$

15 where  $\mathbf{B} \Xi_i \in \mathbb{R}^{m \times q}$  contains  $q$  columns of  $\mathbf{B}$  corresponding to the failed sensors, and  $\mathbf{f}_i(t) \in \mathbb{R}^q$  is a vector of the fault magnitudes. Note that the columns of  $\mathbf{B} \Xi_i$  can be linearly dependent. Performing a singular value decomposition (a matrix decomposition well known to those skilled in the art) on  $\mathbf{B} \Xi_i$  and keeping only non-zero singular values yields

$$\begin{aligned} 20 \quad \mathbf{e}(t) &= \mathbf{e}^*(t) + \mathbf{U}_q \mathbf{D}_q \mathbf{V}_q^T \mathbf{f}_i(t) \\ &= \mathbf{e}^*(t) + \mathbf{U}_q \mathbf{f}_q(t) \end{aligned} \quad (24)$$

where

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$$\mathbf{f}_q(t) = \mathbf{D}_q \mathbf{V}_q^T \mathbf{f}_i(t) \quad (25)$$

To design  $\mathbf{w}_q$  for multiple sensor faults,  $\mathbf{w}_q$  is chosen in the orthogonal complement of  $\mathbf{U}_q$ , that is

$$\mathbf{w}_q = (\mathbf{I} - \mathbf{U}_q \mathbf{U}_q^T) \mathbf{z}_q \in S_{\mathbf{w}_q} \quad (26)$$

5 similar to the single sensor fault case. Furthermore, the following objective is maximized:

$$\max_{\mathbf{z}_q} \|\mathbf{z}_q^T (\mathbf{I} - \mathbf{U}_q \mathbf{U}_q^T) \mathbf{B}^o\|^2 = \max_{\mathbf{z}_q} \|\mathbf{z}_q^T \mathbf{B}_q^o\|^2 \quad (27)$$

subject to

$$\|(\mathbf{I} - \mathbf{U}_q \mathbf{U}_q^T) \mathbf{z}_q\| = 1 \quad (28)$$

10 where

$$\mathbf{B}_q^o = (\mathbf{I} - \mathbf{U}_q \mathbf{U}_q^T) \mathbf{B}^o \quad (29)$$

After using a Lagrange multiplier,  $\mathbf{z}_q$  is found to be the solution to the following equation:

$$\mathbf{B}_q^o \mathbf{B}_q^{oT} \mathbf{z}_q = \lambda (\mathbf{I} - \mathbf{U}_q \mathbf{U}_q^T) \mathbf{z}_q \quad (30)$$

15 From 29 we obtain

$$(\mathbf{I} - \mathbf{U}_q \mathbf{U}_q^T) (\mathbf{B}_q^o \mathbf{B}_q^{oT} \mathbf{z}_q - \lambda \mathbf{z}_q) = \mathbf{0}$$

or

$$\mathbf{B}_q^o \mathbf{B}_q^{oT} \mathbf{z}_q = \lambda \mathbf{z}_q \quad (31)$$

Therefore,  $\mathbf{z}_q$  is simply the eigenvector of  $\mathbf{B}_q^o \mathbf{B}_q^{oT}$  associated with the largest 20 eigenvalue.

### V.3.4 COMPARISON TO CONVENTIONAL STRUCTURED RESIDUAL APPROACH

The conventional structured residual approach (Gertler and Singer, "A new structural framework for parity equation based failure detection and isolation", *Automatica* 26:381-388, 1990, and Gertler and Singer, "Augmented models for 5 statistical fault isolation in complex dynamic systems", *Proceedings of the American Control Conference*, pp317-322, 1985) chooses  $w_i$  to be insensitive to a particular fault of interest, but it does not maximize the sensitivity to other faults. In a typical structured residual design, the selecting of  $w_i$  is not unique and is somewhat arbitrary. The arbitrariness in this design leads to a sub-optimal solution that does not maximize 10 the potential to isolate faults. The SRAMS approach of the present invention embodies a unique design of  $w_i$  that maximizes the sensitivity to other faults while being insensitive to the fault of interest.

### V.3.5 TRANSFORMATIONS MAINTAINED BY THE STRUCTURED RESIDUAL UNIT

15 In the preferred embodiment of the invention, the *Structured Residual Unit* maintains a core set of structured residual transforms corresponding to single sensor faults as described in section V.3.2. These core structured residual transforms form the initial working set of structured residual transforms 132 and associated fault estimation transforms 134.

20 When one or more sensors measurements 108 from the DCS are marked as bad on input to the sensor validator, a new working set of structured residual transforms, and associated fault estimation transforms, is created by the *Structured Residual Unit*. These are as follows: if  $b$  sensors are marked as bad on input, then  $n-b+1$  new structured residual transforms are designed. The first structured residual 25 transform is designed with a  $\Xi$  that selects the columns of the identity matrix corresponding to the  $b$  bad sensors; this structured residual transform is insensitive to these bad sensor values but is sensitive to faults in any of the other sensors. The remaining  $n-b$  structured residual transforms are designed with a  $\Xi$  which selects the columns of the identity matrix correspond to the  $b$  bad sensors plus one more column 30 corresponding to each other sensor in turn. This allows the identification of a further faulty sensor in addition to those marked as bad on input.

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Other structured residual transforms can optionally be designed and added to the working set. For example, a set of transforms based on a  $\Xi$  that selects all pairs of columns from the identity matrix. This allows identification of pairs of simultaneous faults. However, a preferred method of detecting multiple faults is to use several 5 sensor validators. For example, in *FIG. 1*, if a process controller 60 uses 5 sensor values as inputs, up to 5 sensor validators 100 can be utilized, one for each input of the controller. Each sensor validator uses one of the inputs together with other redundant sensor measurements that are not input to the process controller.

Another scenario is to have several sensor validators, each optimized for 10 detection and identification of faults in particular sensors, feeding another sensor validator that is optimized for reconstruction.

#### V.4 DETECTION UNIT

The *Detection Unit 140* monitors the correlation structure of the pre-processed sensor values by calculating a detection index 142 based on the current equation error. 15 If this detection index exceeds a threshold 144 based on a statistically inferred confidence limit, a detection event 148 is generated, and the *Identification Unit* is activated. In the preferred embodiment a filtered normalized fault detection index (*NFFDI*) is used as described below.

##### V.4.1 FAULT DETECTION INDEX

20 The fault detection index (*FDI*) is defined as follows

$$FDI = \|e(t)\|^2 = \|e^*(t) + B\Xi_i f_i(t)\|^2 \quad (7)$$

When no fault is present,  $FDI = \|e^*(t)\|^2 = \|Bx^*(t)\|^2$ . Therefore, the detection alarm threshold for *FDI* is actually the confidence limit for  $\|e^*(t)\|^2$ .

##### V.4.2 NORMALIZED FAULT DETECTION INDEX

25 In practical industrial processes, the process variables  $x^*(t)$  typically are not normally distributed. However, the equation error  $e^*(t)$  128 contains mainly measurement noise and therefore can be considered zero mean Gaussian noise. As a

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consequence  $\mathbf{e}^*(t)^T \mathbf{R}_e^{-1} \mathbf{e}^*(t)$  satisfies a  $\chi^2$  distribution with  $m$  degrees of freedom, where  $\mathbf{R}_e = E\{\mathbf{e}(t)\mathbf{e}^T(t)\}$  is the equation error covariance matrix. Thus defining the normalized fault detection index as

$$NFDI \equiv \mathbf{e}(t)^T \mathbf{R}_e^{-1} \mathbf{e}(t)$$

5 the detection alarm threshold for  $d_\alpha$  for  $NFDI$  can be determined, in a manner well known to those skilled in the art, for any significance level  $\alpha$  using knowledge of the  $\chi^2$  distribution.

Note that  $NFDI \equiv \|\eta(t)\|^2$  where  $\eta(t) = \mathbf{R}_e^{-\frac{1}{2}} \mathbf{e}(t)$  and  $\mathbf{R}_e^{-\frac{1}{2}}$  is the matrix square root of the inverse equation error covariance matrix.  $\mathbf{R}_e^{-\frac{1}{2}}$  has the effect of 10 decorrelating the equation error.

#### V.4.3 NORMALIZED FILTERED FAULT DETECTION INDEX

In the preferred embodiment, an exponentially weighted moving average (EWMA) filter is applied to the equation errors in order to reduce the effect of transients and noise in the measured data:

15

$$\bar{\mathbf{e}}(t) = \gamma \bar{\mathbf{e}}(t-1) + (1-\gamma) \mathbf{e}(t) \quad 0 \leq \gamma < 1 \quad (32)$$

It directly follows that

$$\bar{\mathbf{e}}(t) = (1-\gamma) \sum_{k=0}^{\infty} \gamma^k \mathbf{e}(t-k)$$

and

$$20 \quad \bar{\eta}(t) = (1-\gamma) \sum_{k=0}^{\infty} \gamma^k \eta(t-k) \quad (33)$$

where

$$\bar{\eta}(t) \equiv \mathbf{R}_e^{-\frac{1}{2}} \bar{\mathbf{e}}(t) \quad (34)$$

The filtered normalized fault detection index 142 is defined as

$$NFFDI = \|\bar{\eta}(t)\|^2 \quad (35)$$

Without faults, since  $\eta(t)$  is normally distributed,  $\bar{\eta}(t)$  is also normally distributed  
5 with  $E\{\bar{\eta}(t)\} = E\{\eta(t)\} = 0$ . However, since the EWMA filter significantly reduces the variance of  $\bar{\eta}(t)$ , the confidence limit  $d_\alpha$  can not be applied to  $\bar{d}_\alpha$  directly. The variance of  $\bar{\eta}(t)$  is given by:

$$\begin{aligned} \text{var}(\bar{\eta}(t)) &= E\{\bar{\eta}^T(t)\bar{\eta}(t)\} \\ &= \frac{1-\gamma}{1+\gamma} E\{\eta^T(t)\eta(t)\} \left(1 + 2 \sum_{k=1}^{\infty} \gamma^k \rho(k)\right) \\ &= \text{var}(\eta(t)) \frac{1-\gamma}{1+\gamma} \left(1 + 2 \sum_{k=1}^{\infty} \gamma^k \rho(k)\right) \end{aligned} \quad (36)$$

where

$$10 \quad \rho(k) = \frac{E\{\eta^T(t)\eta(t-k)\}}{E\{\eta^T(t)\eta(t)\}} \quad (37)$$

is an autocorrelation function. If  $\eta(t)$  were independently and identically distributed,  $\rho(k)$  would be 0 for any  $k > 0$ . However, for practical data, this condition is hardly satisfied due to dynamic transients. The non-zero  $\rho(k)$  on the right hand side of equation 36 will contribute to the determination of the detection alarm threshold for 15  $\bar{d}_\alpha$ . Since the threshold for  $\|\eta(t)\|^2$  is  $d_\alpha$ , from equation 36, it is straightforward that the detection alarm threshold 144 for  $\|\bar{\eta}(t)\|^2$  is:

$$\bar{d}_\alpha = d_\alpha \left(1 + 2 \sum_{k=1}^{\infty} \gamma^k \rho(k)\right) \frac{1-\gamma}{1+\gamma} \quad (38)$$

Notice that  $|\rho(k)| \leq 1$ , and therefore

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$$\begin{aligned}
 \bar{d}_\alpha &\leq d_\alpha \left( 1 + 2 \sum_{k=1}^{\infty} \gamma^k |\rho(k)| \right) \frac{1-\gamma}{1+\gamma} \\
 &\leq d_\alpha \left( 1 + 2 \sum_{k=1}^{\infty} \gamma^k \right) \frac{1-\gamma}{1+\gamma} \\
 &= d_\alpha \left( 1 + 2 \frac{\gamma}{1-\gamma} \right) \frac{1-\gamma}{1+\gamma} \\
 &= d_\alpha
 \end{aligned} \tag{39}$$

Therefore, the threshold for *NFFDI* is normally smaller than that for *NFDI*. In practice,  $\rho(k)$  decays to zero after some time  $k$ ; hence, the *Detection Unit* only maintains a fixed number of terms in order to calculate  $\bar{d}_\alpha$ . The significance  $\alpha$  is an 5 adjustable parameter of the *Detection Unit*.

*FIG. 4* shows how the *NFFDI* rapidly increases on the introduction of a fault.

## V.5 IDENTIFICATION UNIT

The *Identification Unit 150* is activated if the *Detection Unit* generates a detection event. The *Identification Unit* calculates several sets of indices **152** that are 10 used to determine if a detected fault can be identified with the failure of one or more sensors. Each set of indices is derived from the working set of structured residuals maintained by the *Structured Residual Unit 130*. In general, if a single index in a set is less than a threshold, whereas all other indices in the set are greater than the threshold, then a fault of known direction is identified. The direction of this fault corresponds to 15 directions that define the structured residual associated with the index. In the most typical case this corresponds to a fault in a single sensor.

In the preferred embodiment of this invention, the *Identification Unit* maintains 3 sets of indices **152** and their associated thresholds **154**. These sets of indices are the Normalized Squared Filtered Structured Residuals (*NSFSR*), the 20 Generalized Likelihood Ratio (*GLR*) indices, and the Normalized Cumulative Variance (*NCUMVAR*) indices. The associated thresholds are denoted by  $\vartheta_{NSFSR}$ ,  $\vartheta_{GLR}$ , and  $\vartheta_{NCUMVAR}$ . A flow diagram that summarizes the fault identification process is shown in *FIG. 2*.

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## V.5.1 NORMALIZED SQUARED FILTERED STRUCTURED RESIDUAL

Ideally, each structured residual  $r_i(t)$  is supposed to be zero or close to zero when no sensor fails. However, due to modeling error, measurement noise and other uncertainties,  $r_i(t)$  is never equal to zero. Therefore, the non-zero confidence limit for 5 each  $r_i(t)$   $i, j = 1, 2, \dots, n$  is determined using statistical techniques.

Without a fault or with the sensor(s) associated with the  $i^{th}$  structured residual being faulty, the  $i^{th}$  structured residual follows a normal distribution,

$$r_i(t) = \mathbf{w}_i^T \mathbf{e}(t) \sim \mathcal{N}(0, \mathbf{w}_i^T \mathbf{R}_e \mathbf{w}_i) \quad i = 1, 2, \dots, n \quad (40)$$

where  $\mathbf{R}_e = E\{\mathbf{e}(t)\mathbf{e}^T(t)\}$  is the equation error covariance matrix.

10 Consequently

$$\frac{r_i^2(t)}{\mathbf{w}_i^T \mathbf{R}_e \mathbf{w}_i} \sim \chi^2(1) \quad i = 1, 2, \dots, n \quad (41)$$

Then, defining the  $i^{th}$  normalized structured residual ( $NSR$ ) as

$$\nu_i(t) \equiv \frac{r_i(t)}{\sqrt{\mathbf{w}_i^T \mathbf{R}_e \mathbf{w}_i}} \sim \mathcal{N}(0, 1) \quad (42)$$

and defining the normalized squared structured residual ( $NSSR$ ) as  $\nu_i^2(t)$ , the 15 confidence limit for  $NSSR$  is  $\chi_\alpha^2(1)$  where  $\alpha$  is the level of significance.

When an EWMA filter is applied to the  $NSR$ , the normalized filtered structured residual ( $NFSR$ ) is

$$\begin{aligned} \bar{\nu}_i(t) &= \gamma \bar{\nu}_i(t-1) + (1-\gamma) \nu_i(t) \\ &= (1-\gamma) \sum \gamma^k \nu_i(t-k) \end{aligned} \quad (43)$$

Without a fault or with the sensor(s) associated with the  $i^{th}$  structured residual being 20 faulty, the  $NFSR$  also follows a normal distribution with

$$E\{\bar{\nu}_i(t)\} = E\{\nu_i(t)\} = 0$$

and

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$$\text{var}(\bar{\nu}_i(t)) = \text{var}(\nu_i(t)) \frac{1-\gamma}{1+\gamma} \left( 1 + 2 \sum_{k=1}^{\infty} \gamma^k \psi_i(k) \right) \quad (44)$$

where

$$\psi_i(k) = \frac{E\{\nu_i(t)\nu_i(t-k)\}}{E\{\nu_i(t)^2\}}$$

is an autocorrelation function.

5 Therefore the alarm threshold for the normalized squared filtered structured residual (*NSFSR*) defined by  $\bar{\nu}_i^2(t)$  has an alarm threshold of

$$\mathcal{G}_{NSFSR}^i \equiv \bar{\eta}_i^{\alpha}(t) = \frac{1-\gamma}{1+\gamma} \left( 1 + 2 \sum_{k=1}^{\infty} \gamma^k \psi_i(k) \right) \chi_{\alpha}^2(1) \quad i = 1, 2, \dots, n \quad (45)$$

If all sensors are normal  $\bar{\nu}_i^2(t)$  is normally below its threshold as indicated by:

$$P\{\bar{\nu}_i^2(t) > \mathcal{G}_{NSFSR}^i\} = \alpha$$

10 If the sensor(s) associated with the  $i^{\text{th}}$  structured residual are faulty, by the SRAMS design,  $\bar{\nu}_i^2(t)$  is not affected by the fault. However, the other residuals,  $\bar{\nu}_j^2(t) j \neq i$ , will increase significantly because their sensitivity to the faults in other sensors is maximized.

Therefore, with a selected level of significance  $\alpha$  and an instant  $t$ , among *NSFSRs*,  
15 the existence of exactly one *NSFSR* that is less than its threshold  $\mathcal{G}_{NSFSR}^i$  identifies a faulty sensor, and generates an identification event **158**. An example of this is shown in *FIG. 7* in which the top window shows the *NSFSRs* that do not correspond to faulty sensor 5 become very large, whereas the bottom window shows the *NSFSR* for sensor 5 remains below its threshold.

20 Since there are often many sensors to be validated, the probability for at least one residual to exceed its threshold is significant, even though the probability for each index to exceed its threshold is small. For example, assuming that there are 20 residuals  $r_i(t) i = 1, 2, \dots, 20$ . The probability for at least one *NSFSR* to exceed its threshold is (assuming  $\alpha = 0.05$ )

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$$P = 1 - (1 - \alpha)^{20} = 1 - 0.95^{20} = 0.642$$

even though all sensors are normal. Therefore, the *NSFSRs* are not used for fault detection. Instead, the *Detection Unit* uses the *NFFDI* to trigger a detection event after which the *Identification Unit* uses the various sets of indices, starting with the 5 *NSFSRs*, to identify the faulty sensors.

Optionally, the *NSFSR* indices can be calculated at each cycle, whether or not the *Detection Unit* has generated a detection event. However, the index sets described in the next two sections accumulate structured residual information since the time of fault detection, so they only make sense after a detection event has been generated.

#### 10 V.5.2 GENERALIZED LIKELIHOOD RATIO INDEX

If a sensor fault incurs significant changes in the mean, e.g., complete failure, bias, or drift, the generalized likelihood ratio (*GLR*) is usually an appropriate test for detecting this (Benveniste, Basseville and Moustakides "The asymptotic local approach to change detection and model validation" *IEEE Trans. Auto. Cont.* 15 **32**(7):538-592, July 1987.

To clarify the following analysis, each structured residual transform is assumed to correspond to a fault in a single sensor. In general, however, the *GLR* indices can be constructed and monitored irrespective of the structured residual design.

20 As shown by equation 42, when no sensor is faulty  $\nu_i(t)$  is zero-mean and normally distributed, with unit variance. However, if the  $j^{\text{th}}$  sensor becomes faulty at instant  $t_f$  it is clear that

$$\nu_i(t) = \frac{\mathbf{w}_i^T \mathbf{e}^*(t)}{\sqrt{\mathbf{w}_i^T \mathbf{R}_e \mathbf{w}_i}} + \frac{\mathbf{w}_i^T \mathbf{b}_j f_j(t)}{\sqrt{\mathbf{w}_i^T \mathbf{R}_e \mathbf{w}_i}} \quad (46)$$

is no longer zero-mean but the variance is unchanged. In other words

$$25 \quad \nu_i(t) \sim \begin{cases} \mathcal{N}(0,1) & \text{if } t < t_f \\ \mathcal{N}(\mu_{ij}, 1) & \text{if } t \geq t_f \end{cases} \quad (47)$$

where

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$$\mu_{ij}(t) = \frac{\mathbf{w}_i^T \mathbf{b}_j f_j(t)}{\sqrt{\mathbf{w}_i^T \mathbf{R}_e \mathbf{w}_i}} \quad (48)$$

It should be noted that  $\mu_{jj} = 0$  by the SRAMS design.

To detect the mean change of  $\nu_i(t)$ , define the following GLR function

$$S'_{t_f}(\mu_{ij}) = \frac{\sum_{k=t_f}^t \nu_i^2(k) - \sum_{k=t_f}^t (\nu_i(k) - \mu_{ij})^2}{t - t_f + 1} \quad (49)$$

5 Differentiating  $S'_{t_f}(\mu_{ij})$  with respect to  $\mu_{ij}$  produces the optimal estimate of  $\mu_{ij}$

$$\hat{\mu}_{ij} = \frac{\sum_{k=t_f}^t \nu_i(k)}{t - t_f + 1} \quad (50)$$

With  $\hat{\mu}_{ij}$ ,  $S'_{t_f}(\mu_{ij})$  is maximized with

$$S'_{t_f}(\hat{\mu}_{ij}) = \hat{\mu}_{ij}^2 \quad (51)$$

If the  $j^{th}$  sensor is faulty,  $\mu_{jj} = 0$ , and  $\nu_j(t) \sim \mathcal{N}(0,1)$ . From equation 50,

10  $\hat{\mu}_{jj}(t) \sim \mathcal{N}(0,1)$

or

$$S'_{t_f}(\hat{\mu}_{jj}) = \hat{\mu}_{jj}^2 \sim \chi^2(1)$$

Therefore, with a selected level of significance  $\alpha$  and an instant  $t$ , among the  $n$  GLRs

$$S'_{t_f}(\hat{\mu}_{1j}), S'_{t_f}(\hat{\mu}_{2j}), \dots, S'_{t_f}(\hat{\mu}_{nj})$$

15 the existence of exactly one GLR that is less than the threshold  $\vartheta_{GLR} = \chi^2_\alpha(1)$  identifies a faulty sensor, and generates an identification event 158.

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### V.5.3 NORMALIZED CUMULATIVE VARIANCE INDEX

If a sensor incurs a precision degradation fault, the *GLR* index set will have difficulty identifying it. To identify the location of precision degradation faults, the mean and variance of the *NSR* is calculated since the time the fault occurred:

$$5 \quad NCUMMEAN_i(t) = \frac{1}{t - t_f + 1} \sum_{k=t_f}^t v_i(k)$$

$$NCUMVAR_i(t) = \frac{1}{t - t_f} \sum_{k=t_f}^t (v_i(k) - NCUMMEAN_i(t))^2$$

Assuming, for clarity of explanation, each structured residual transform corresponds to a fault in a single sensor, when either no sensor or the  $i^{th}$  sensor fails,

$$NCUMVAR_i(t) \sim \frac{1}{t - t_f} \chi^2(t - t_f - 1)$$

Therefore, with a selected level of significance  $\alpha$  and an instant  $t$ , among the  $n$  10  $NCUMVARs$ , the existence of exactly one  $NCUMVAR$  that is less than the threshold  $\vartheta_{NCUMVAR} = \frac{1}{t - t_f} \chi_{\alpha}^2(t - t_f - 1)$  identifies a sensor with precision fault, and generates an identification event **158**.

### V.6 ESTIMATION UNIT

The *Estimation Unit 160* is only active if the *Identification Unit 150* has 15 generated an identification event **158**. The *Estimation Unit* then optimally estimates the fault magnitude based on the model, the faulty data, and the matrix  $\Xi_i$ , corresponding to the structured residual transform that was instrumental in generating the identification event. This optimal estimation is based on public domain prior art as described, for example, Martens and Naes “*Multivariate Calibration*”, *John Wiley and Sons, New York, 1989*.

The optimal estimation is achieved by choosing a time function  $f_q(t)$  in the direction  $U_q$  where, as in equation 24,  $U_q$  is the orthogonal left hand side matrix of a singular value decomposition on  $B\Xi_i$  in which only non-singular values are maintained. In other words, minimize

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$$J = \|e^*(t)\|^2 = \|e(t) - U_q f_q(t)\|^2 \quad (52)$$

A least square solution to this problem leads to:

$$\hat{f}_q(t) = U_q^T e(t) \quad (53)$$

The original fault magnitude  $f_i(t)$  can be estimated using equation 25:

$$5 \quad \hat{f}_i(t) = (\mathbf{D}_q \mathbf{V}_q^T)^+ \hat{f}_q(t) \quad (54)$$

where  $(\ )^+$  is the Moore-Penrose pseudo-inverse, well known to those skilled in the art. The *Structured Residual Unit* 130 maintains the estimation matrix 134

$$\Xi_i (\mathbf{D}_q \mathbf{V}_q^T)^+ \mathbf{U}_q^T \quad (55)$$

for each structured residual it maintains. The estimation matrix corresponding to the 10 structured residual that identified the fault is used to map the equation error 128 to an estimate of the fault vector in the pre-processed sensor value space 136. The *Estimation Unit* then applies the inverse scaling 116 from the *Pre-processing Unit* resulting in an estimate of the fault vector in the original sensor space 168:

$$\hat{f}_u(t) = \text{diag} \left( \frac{1}{s_1} \quad \frac{1}{s_2} \quad \Lambda \quad \frac{1}{s_2} \right) \Xi_i (\mathbf{D}_q \mathbf{V}_q^T)^+ \mathbf{U}_q^T e(t) \quad (56)$$

15 *FIG. 5* shows the output of the *Estimation Unit* for a bias fault in Sensor 2. *FIG. 6* shows the output of the *Estimation Unit* for a drift fault in Sensor 5. In both cases the fault size is accurately estimated.

## V.7 REPLACEMENT UNIT

The *Replacement Unit* 170 simply takes the estimate of the fault vector in the 20 original sensor space 168 as estimated by the *Estimation Unit* (equation 56) and subtracts the estimated fault from the measured vector of sensor values 108 to produce a vector of replacement values 178:

$$\hat{u}(t) = u(t) - \hat{f}_u(t) \quad (57)$$

The *Replacement Unit* is only active if *Estimation Unit* 160 is active, which in turn is 25 only active if the *Identification Unit* 150 has generated an identification event 158. In

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addition, as a safety feature, an operator of the apparatus can explicitly disable (172) the *Replacement Unit*.

## V.8 CLASSIFICATION UNIT

The *Classification Unit 180* calculates diagnostic information as to the type of 5 sensor fault. Specifically, four types of fault are considered: *Complete Failure, Bias, Drift, and Precision Loss*.

The *Classification Unit* is only active when an identification event 158 has occurred. From the point when a sensor is first identified as being faulty, a buffer of measured sensor values is maintained and a buffer of estimated fault sizes for that 10 sensor is also maintained. The information in these two buffers is analyzed and used to classify the type of fault for that sensor. The analysis primarily makes use of statistical inference, so a significance level  $\alpha$  is required which is an adjustable parameter of the *Classification Unit*.

For clarity of explanation, assume that a single sensor fault has been identified 15 by the *Identification Unit 150*. A flow diagram of the classification logic is shown in *FIG. 3*.

### V.8.1 CLASSIFICATION TYPE: COMPLETE FAILURE

*Complete failure* is determined by performing a regression analysis on the faulty sensor's measured values 108, and is indicated by the statistical inference that 20 the regression line fits well, and has zero slope.

Let  $\{k, u_i(k) | k = t_{id}, \dots, t\}$  be the sequence of points for which the regression line is calculated, where  $t_{id}$  is the point at which the sensor was identified as faulty, and  $t$  is the current point in time.

Using standard least squares regression, which minimizes the residual between 25 the points and the best fit line, the slope  $\beta$  and y-intercept  $\alpha$  are estimated as:

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$$\hat{\beta} = \frac{\sum_{k=t_{id}}^t (k - \bar{k})(u_i(k) - \bar{u}_i)}{\sum_{k=t_{id}}^t (k - \bar{k})^2} \quad (58)$$

$$\hat{\alpha} = \bar{u}_i - \hat{\beta} \bar{k}$$

where

$$\bar{k} = \frac{1}{t - t_{id} + 1} \sum_{k=t_{id}}^t k \quad (59)$$

$$\bar{x}_i = \frac{1}{t - t_{id} + 1} \sum_{k=t_{id}}^t u_i(k)$$

To test if the slope is statistically equal to 0, construct the following statistic:

$$5 \quad |t_{\beta}| = \frac{|\hat{\beta}|}{SD(\hat{\beta})} \quad (60)$$

where the standard deviation of  $\hat{\beta}$  is given by

$$SD(\hat{\beta}) = \frac{\sigma}{\sqrt{\sum_{k=t_{id}}^t (k - \bar{k})^2}} \quad (61)$$

and the standard deviation  $\sigma$  of the residual is estimated by

$$\hat{\sigma} = \sqrt{\frac{\sum_{k=t_{id}}^t \hat{e}_i^2(k)}{t - t_{id} - 1}} \quad (62)$$

10 where

$$\hat{e}_i(k) = u_i(k) - (\beta k + \alpha)$$

is the residual error.

The statistic given in equation 60 satisfies Student's t distribution with

 $t - t_{id} - 1$  degrees of freedom (see, for example Birkes and Dodge "Alternative15 Methods of Regression", *John Wiley & Sons* 1993).

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Goodness of fit of the regression line is determined by the linear correlation coefficient exceeding a specified threshold.

#### V.8.2 CLASSIFICATION TYPE: BIAS

5 *Bias* is determined by performing a regression analysis on the faulty sensor's fault size estimates 168 as calculated by *Estimation Unit 160*, and is indicated by the statistical inference that the regression line fits well, has zero slope, and has non-zero bias.

10 Let  $\{k, f_i(k) | k = t_{id}, \dots, t\}$  be the sequence of points for which the regression line is calculated, where  $t_{id}$  is the point at which the sensor was identified as faulty, and  $t$  is the current point in time. Testing for zero slope is the same as for classifying *Complete Failure*, except that the fault size sequence  $f_i(k)$  replaces the sensor value sequence  $u_i(k)$ . Goodness of fit of the regression line is determined by the linear correlation coefficient exceeding a specified threshold.

To test for non-zero bias, calculate the statistic:

$$15 \quad |t_\alpha| = \frac{|\bar{\alpha}|(t - t_{id} + 1)}{\sigma} \quad (63)$$

which also satisfies Student's t distribution with  $t - t_{id} - 1$  degrees of freedom.

#### V.8.3 CLASSIFICATION TYPE: DRIFT

20 *Drift* is determined by performing a regression analysis on the faulty sensor's fault size estimates 168 as calculated by *Estimation Unit 160*, and is indicated by the statistical inference that the regression line fits well, and has non-zero slope.

#### V.8.4 CLASSIFICATION TYPE: PRECISION LOSS

25 *Precision Loss* is determined by performing a regression analysis on the faulty sensor's fault size estimates 168 as calculated by *Estimation Unit 160*, and is indicated by the statistical inference that the regression line does not fit well, and has zero slope, and has zero bias.

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*Precision Loss* is also indicated if the identification event 158 was generated due to the *NCUMVAR* test of section V.5.3.

**CLAIMS:**

1. An apparatus for detecting one or more sensor faults in a measured process, wherein the improvement comprises:
  - a per-processing unit for receiving a working vector of signals including measured sensor values, the pre-processing unit having means for normalizing the measured sensor values, resulting in pre-processed sensor values;
  - a model unit coupled to the pre-processing unit, which converts pre-processed sensor values to equation error values that contain mainly measurement noise;
  - a structured residual unit coupled to the model unit, which contains a plurality of transforms, referred to as structured residual transforms, each such transform converting equation error values to a structured residual value, and each such transform is optimally designed to be insensitive to faults in a subset of sensors;
  - a detection unit coupled to the model unit, the detection unit monitoring the relationship among the equation error values, occurrence of a significant deviation of said relationship from expected relationship resulting in a detection event;
  - an identification unit coupled to the structured residual unit and the detection unit, the identification unit being activated by a detection event, and using the structured residual values to determine if one or more sensors are faulty, said determination resulting in an identification event;
  - an estimation unit coupled to the pre-processing unit, the structured residual unit and the identification unit, the estimation unit being activated by an identification event, and estimating fault sizes for each of the identified faulty sensors;
  - a replacement unit coupled to the estimation

unit, the replacement unit calculating replacement values for the faulty measured sensor values in the working signal values by subtracting the estimated fault size from the corresponding measured sensor value for all identified faults; and

a classification unit coupled to the estimation unit, the classification unit being active when the estimation unit is active, and classifying the identified sensor faults into a fixed set of fault types.

2. The apparatus of claim 1 wherein:

the normalizing in the pre-processing units is achieved by scaling and offsetting the measured sensor values, and wherein:

the working vector signals includes known status information about the measured sensor values, and wherein:

the converting of the pre-processed sensor values in the model unit is achieved by multiplying the pre-processed sensor values by a matrix to produce the equation error.

3. The apparatus of claim 2 wherein the matrix is derived from one of the following:

(i) the residual part of a principal component analysis;

(ii) a residual part of a set of partial least squares models, one for each sensor value; and

(iii) mass balance or energy balance of the measured process.

4. The apparatus of claim 1 wherein:

a subset of sensors defining each transform includes at least all sensors of known bad status.

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5. The apparatus of claim 1 wherein the detection unit monitors the relationship among the equation error values by:
  - calculating a detection index which is a function of the equation errors; and
  - comparing said detection index to a threshold in order to detect occurrence of a significant deviation of said relationship from expected relationship, wherein, further, the detection index is obtained by summing squared values of the equation error values.
6. The apparatus of claim 5 wherein:
  - the equation error is multiplied by a matrix to decorrelate the equation error values, resulting in decorrelated equation error values; and
  - the detection index is obtained by summing the squared values of the decorrelated equation error values, wherein:
    - the threshold is determined using statistical techniques.
7. The apparatus of claim 6 wherein:
  - the detection index is filtered, at least according to time, in order to smooth out the effects of transients and noise, resulting in a filtered detection index; and
  - the filtered detection index is used in place of said detection index to monitor a relationship among the equation error values; and wherein:
    - the filtered detection index is compared to a threshold in order to detect occurrence of a significant deviation of said relationship from expected relationship.
8. The apparatus of claim 7 wherein:
  - the detection index is filtered by applying an exponentially weighted moving average filter, wherein

a threshold for the filtered detection index is calculated from the detection index threshold using an auto-correlation function.

9. The apparatus of claim 5 wherein:
  - the detection index is filtered, at least according to time, in order to smooth out the effects of transients and noise, resulting in a filtered detection index; and
  - the said filtered detection index is used in place of said detection index to monitor a relationship among the equation error values; and wherein
  - the said filtered detection index is compared to a threshold in order to detect occurrence of a significant deviation of said relationship from expected relationship.
10. The apparatus of claim 9 wherein:
  - the detection index is filtered by applying an exponentially weighted moving average filter, wherein a threshold for the filtered detection index is calculated from the detection index threshold using an auto-correlation function.
11. The apparatus of claim 1 wherein:
  - the identification unit compares each structured residual value to a corresponding threshold;
  - an identification event occurs if the value of all but one structured residual value, referred to as the identified structured residual value, exceeds its corresponding threshold; and
  - the determined faulty sensors are a subset of sensors for which, by design, a structured residual transform corresponding to an identified structured residual value is insensitive to the presence of faults in said subset.

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12. The apparatus of claim 1 wherein:
  - the identification unit applies conversion operations to the structured residual values resulting in converted structured residual indices;
  - the identification unit compares each converted structured residual index to a corresponding threshold;
  - an identification event occurs if the converted structured residual index of all but one structured residual index, referred to as the identified converted structured residual index, exceeds its corresponding threshold; and
  - the determined faulty sensors are a subset of sensors for which, by design, a structured residual transform corresponding the converted structured residual index is insensitive to the presence of faults in said subset, wherein:
    - the conversion operation includes the operations of squaring and scaling.
13. The apparatus of claim 12 wherein:
  - the conversion operation includes applying an exponentially weighted moving average filter in time, wherein the threshold for each converted structured residual index is calculated from the corresponding structured residual threshold using an auto-correlation function.
14. The apparatus of claim 1 wherein:
  - the identification unit applies accumulating operations to the structured residual values resulting in accumulated structured residual indices, said operations accumulating since the time of the fault detection event;
  - the identification unit compares each accumulated structured residual index to a corresponding threshold;

an identification event occurs if the accumulated structured residual index of all but one structured residual, referred to as the identified accumulated structured residual index, exceeds its corresponding threshold; and

the determined faulty sensors are the subset of sensors for which, by design, the structured residual transform corresponding to the identified accumulated structured residual index is insensitive to the presence of faults in said subset, wherein the accumulating operation calculates a generalized likelihood ratio index that is designed to detect significant changes in the statistical mean of the structured residuals since the time of the fault detection event.

15. The apparatus of claim 1 wherein:

the classification unit calculates a plurality of regression lines, one for each identified faulty sensor, each such regression line being calculated using the measured sensor values for the corresponding faulty sensor since the time of identification, resulting in a plurality of sensor value regression lines;

the classification unit calculates a plurality of regression lines, one for each identified faulty sensor, each such regression line being calculated using estimated fault sizes for the corresponding faulty sensor since the time of identification, resulting in a plurality of fault size regression lines; and

the classification unit uses slope, bias, and residual information from sensor value regression lines and fault size regression lines to classify the identified sensor faults into a fixed set of fault types.

16. The apparatus of claim 1 wherein:  
each transform of the structured residual unit is designed to be insensitive to faults in a subset of sensors, but maximally sensitive to faults in all other sensors.
17. The apparatus of claim 1 wherein:  
each transform of the structured residual unit is designed to be insensitive to a fault a single sensor, but maximally sensitive to faults in all other sensors.
18. A computer method for detecting one or more sensor faults in a measured process wherein the improvement comprises the steps of:  
receiving a working vector of signals including measured sensor values, and preprocessing the measured sensor values, resulting in pre-processed sensor values;  
converting the pre-processed sensor values to equation error values that contain mainly measurement noise;  
applying a plurality of transforms to the equation error values resulting in a plurality of structured residual values, said transforms referred to as structured residual transforms and optimally designed to be insensitive to faults in a subset of sensors;  
monitoring a relationship among the equation error values, an occurrence of a significant deviation of said relationship from expected relationship resulting in a detection event;  
in the case that a detection event occurs, using the structured residual values to determine if one or more sensors are faulty, said determination resulting in an identification event;

in the case that an identification event occurs, estimating fault sizes for each of the identified faulty sensors;

in the case that an identification event occurs, replacing faulty measured sensor values in the working signal with corrected values by subtracting the estimated fault size from the corresponding measured sensor value for all identified faults; and

in the case that an identification event occurs, classifying the identified sensor faults into a fixed set of fault types.

19. The method of claim 18 wherein:

the step of pre-processing the measured sensor values is achieved by scaling and offsetting.

20. The method of claim 18 wherein:

the working signal includes known status information about the measured sensor values.

21. The method of claim 18 wherein:

the step of converting the pre-processed sensor values to equation error values is achieved by multiplying the pre-processed sensor values by a matrix, wherein the matrix is derived from one of the following:

- (i) the residual part of a principal component analysis;
- (ii) the residual part of a set of partial least squares models, one for each sensor value; and
- (iii) mass balance or energy balance of the measured process.

22. The method of claim 18 wherein:

each structured residual transform consists of a vector of coefficients that are applied as a dot product to the equation error, wherein:

each structure residual transform is designed to be insensitive to faults in a subset of sensors, but maximally sensitive to faults in all other sensors not in the subset.

23. The method of claim 18 wherein the step of monitoring the relationship among the equation error values consists of:

calculating a detection index which is a function of the equation errors; and

comparing said detection index to a threshold in order to detect occurrence of a significant deviation of said relationship from expected relationship.

24. The method of claim 23 wherein:

each of said equation error values is multiplied by a matrix to decorrelate the equation error values, resulting in decorrelated equation error values; and

the detection index is obtained by summing the squared values of the decorrelated equation error values, wherein:

the threshold is determined using statistical techniques.

25. The method of claim 24 wherein:

the detection index is filtered, at least according to time, in order to smooth out the effects of transients and noise, resulting in a filtered detection index;

said filtered detection index is used in place of the detection index to monitor the relationship among the equation error values; and

said filtered detection index is compared to a threshold in order to detect occurrence of a significant deviation of said relationship from

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expected relationship, wherein further, the detection index is filtered by applying an exponentially weighted moving average filter.

26. The method of claim 18 wherein the step of determining if one or more sensors are faulty consists of:
  - comparing each structured residual value to a corresponding threshold; and
  - generating an identification event if the value of all but one structured residual value, referred to as the identified structured residual value, exceeds its corresponding threshold; and
  - determining that the faulty sensors are the subset of sensors for which, by design, the structured residual transform corresponding to the identified structured residual value is insensitive to the presence of faults in said subset.
27. The method of claim 18 wherein conversion operations are applied to the structured residual values resulting in converted structured residual indices and the step of determining if one or more sensors are faulty consists of:
  - comparing each converted structured residual index to a corresponding threshold;
  - generating an identification event if the converted structured residual index of all but one structured residual, referred to as the identified converted structured residual index, exceeds its corresponding threshold; and
  - determining that the faulty sensors are the subset of sensors for which, by design, the structured residual transform corresponding to the converted structured residual index is insensitive to the presence of faults in said subset, wherein, the conversion operation includes the operations of squaring and scaling.

28. The method of claim 18 wherein accumulating operations are applied to the structured residual values resulting in accumulated structured residual indices, said operations accumulating since the time of the fault detection event, and the step of determining if one or more sensors are faulty consists of:

comparing each accumulated structured residual index to a corresponding threshold;

generating an identification event if the accumulated structured residual index of all but one structured residual, referred to as the identified accumulated structured residual index, exceeds its corresponding threshold; and

determining that the faulty sensors are the subset of sensors for which, by design, the structured residual transform corresponding to the identified accumulated structured residual index is insensitive to the presence of faults in said subset, wherein, the accumulating operation calculates a generalized likelihood ratio index that is designed to detect significant changes in the statistical mean of the structured residuals since the time of the fault detection event.

29. The method of claim 18 wherein the step classifying the identified sensor faults into a fixed set of fault types is achieved by:

calculating a plurality of regression lines, one for each identified faulty sensor, each such regression line calculated using the measured sensor values for the corresponding faulty sensor from the time of identification, resulting in a plurality of sensor value regression lines;

calculating a plurality of regression lines, one for each identified faulty sensor, each such regression line calculated using estimated fault sizes for the corresponding faulty sensor from the time of

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identification, result in a plurality of fault size regression lines; and


using slope, bias, and residual information from sensor value regression lines and fault size regression lines to classify the identified sensor faults into a fixed set of fault types.

30. The method of claim 18 wherein:

each structured residual transform is designed to be insensitive to faults in a subset of sensors, but maximally sensitive to faults in all other sensors.

31. The method of claim 18 wherein:

each structured residual transform is designed to be insensitive to a fault in a single sensor, but maximally sensitive to faults in all other sensors.



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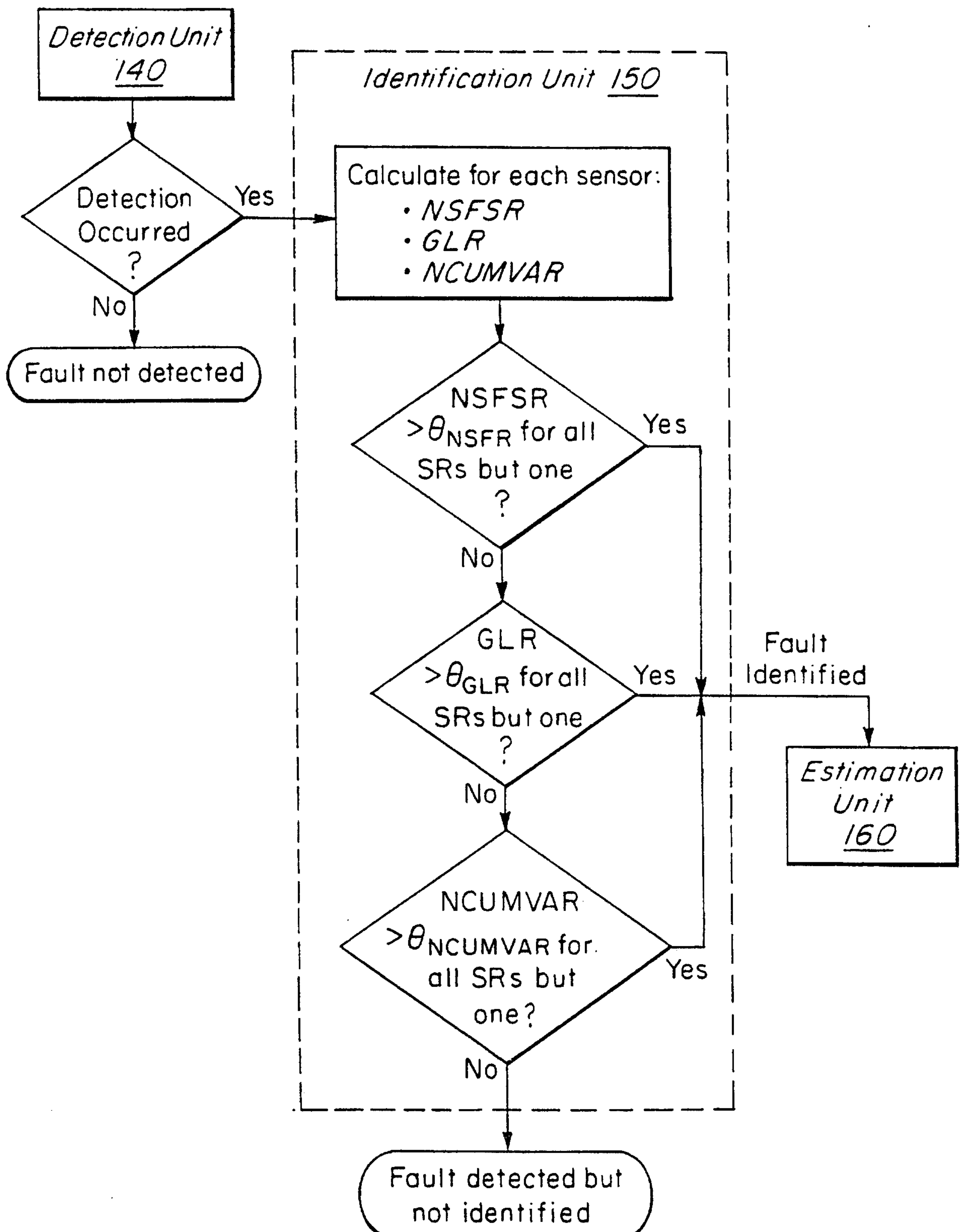


FIG. 2

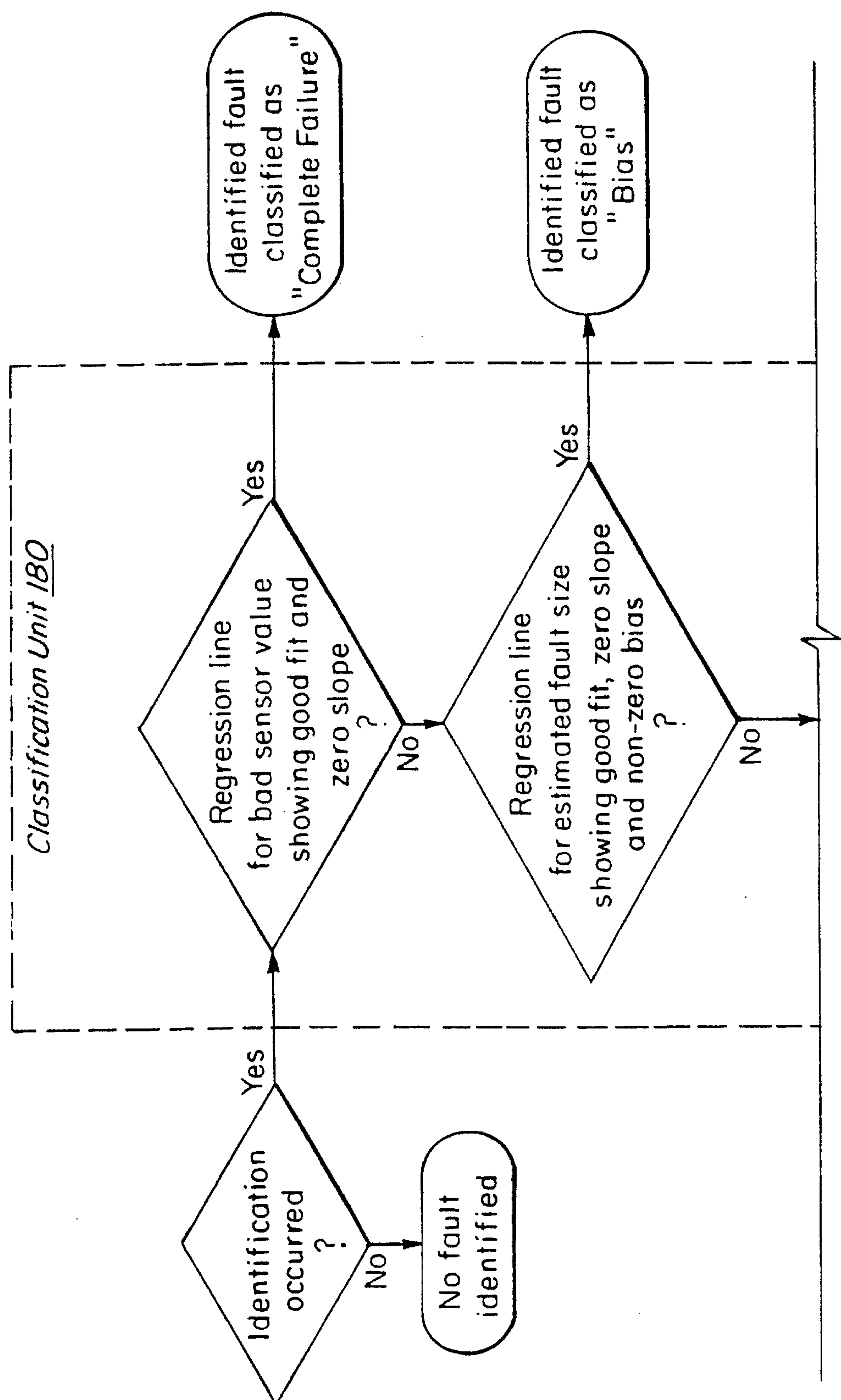


FIG. 3A

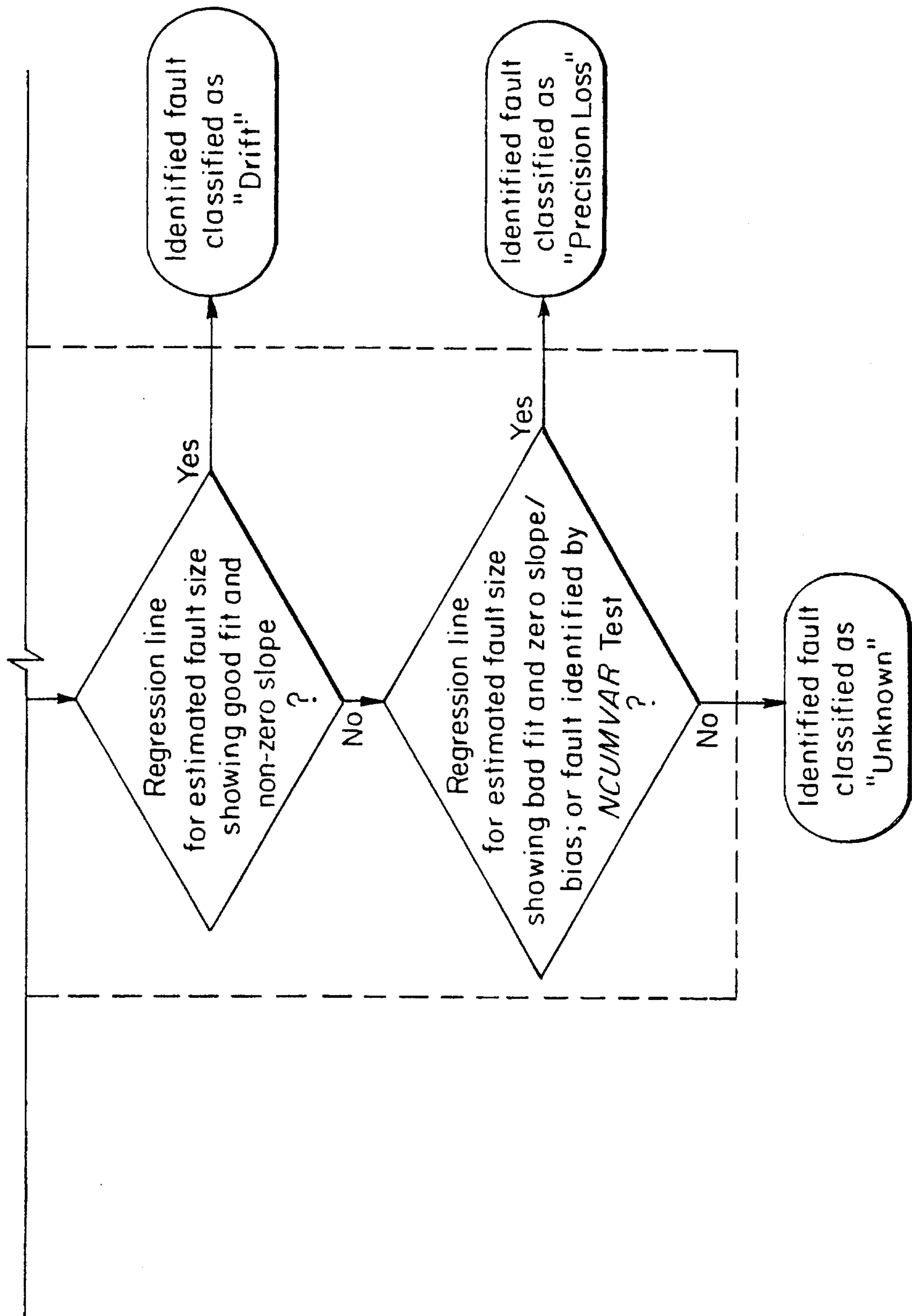


FIG. 3B

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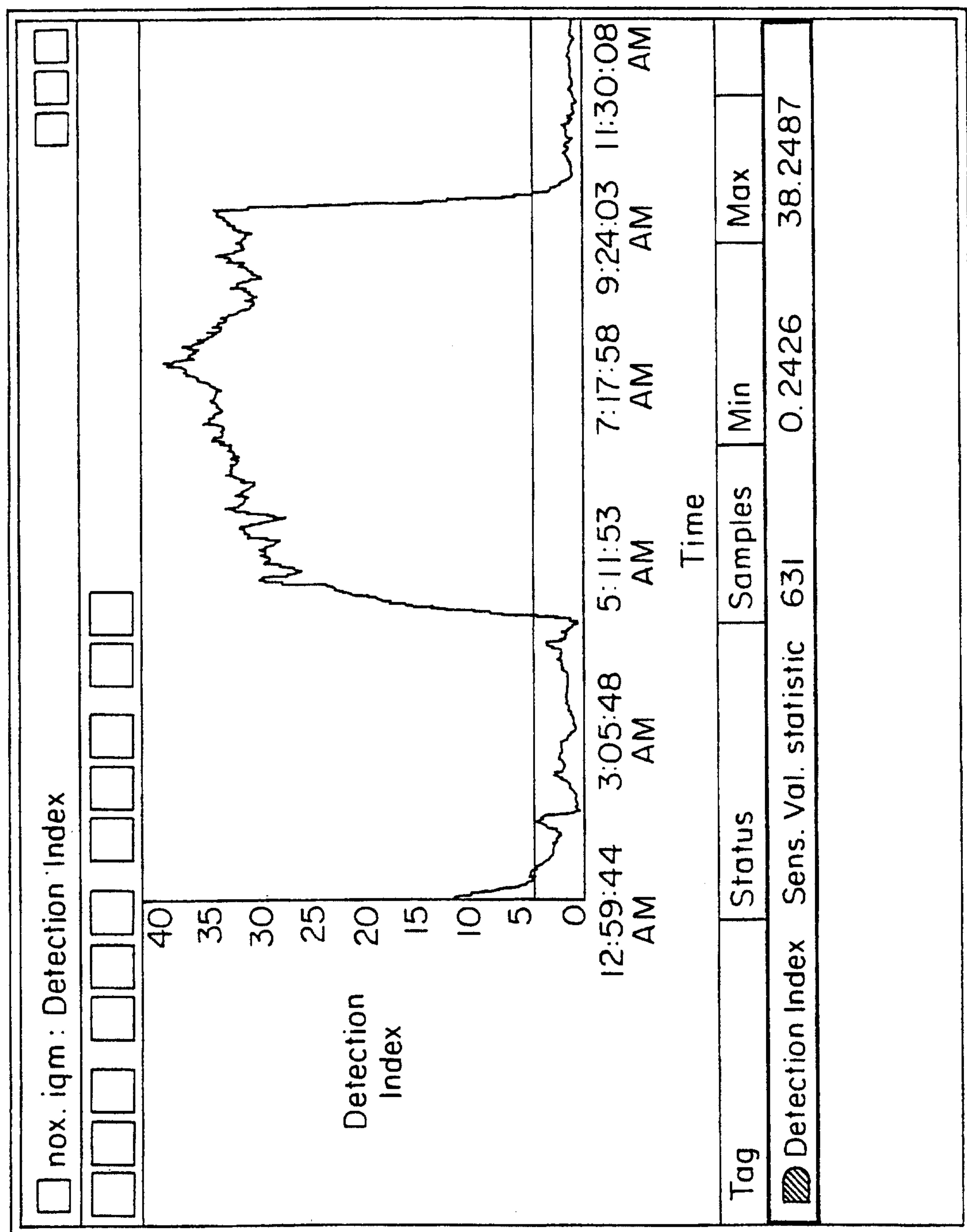


FIG. 4

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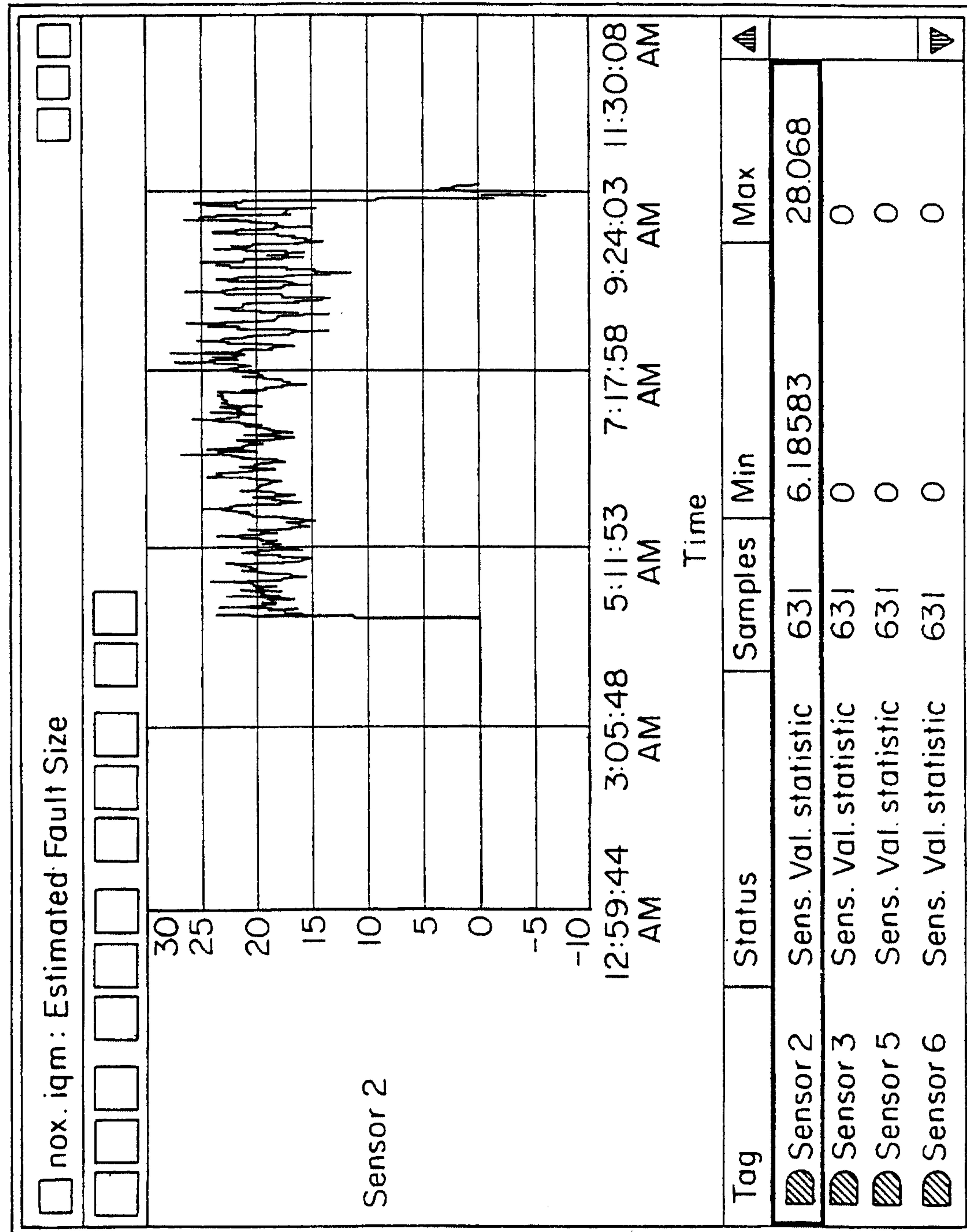


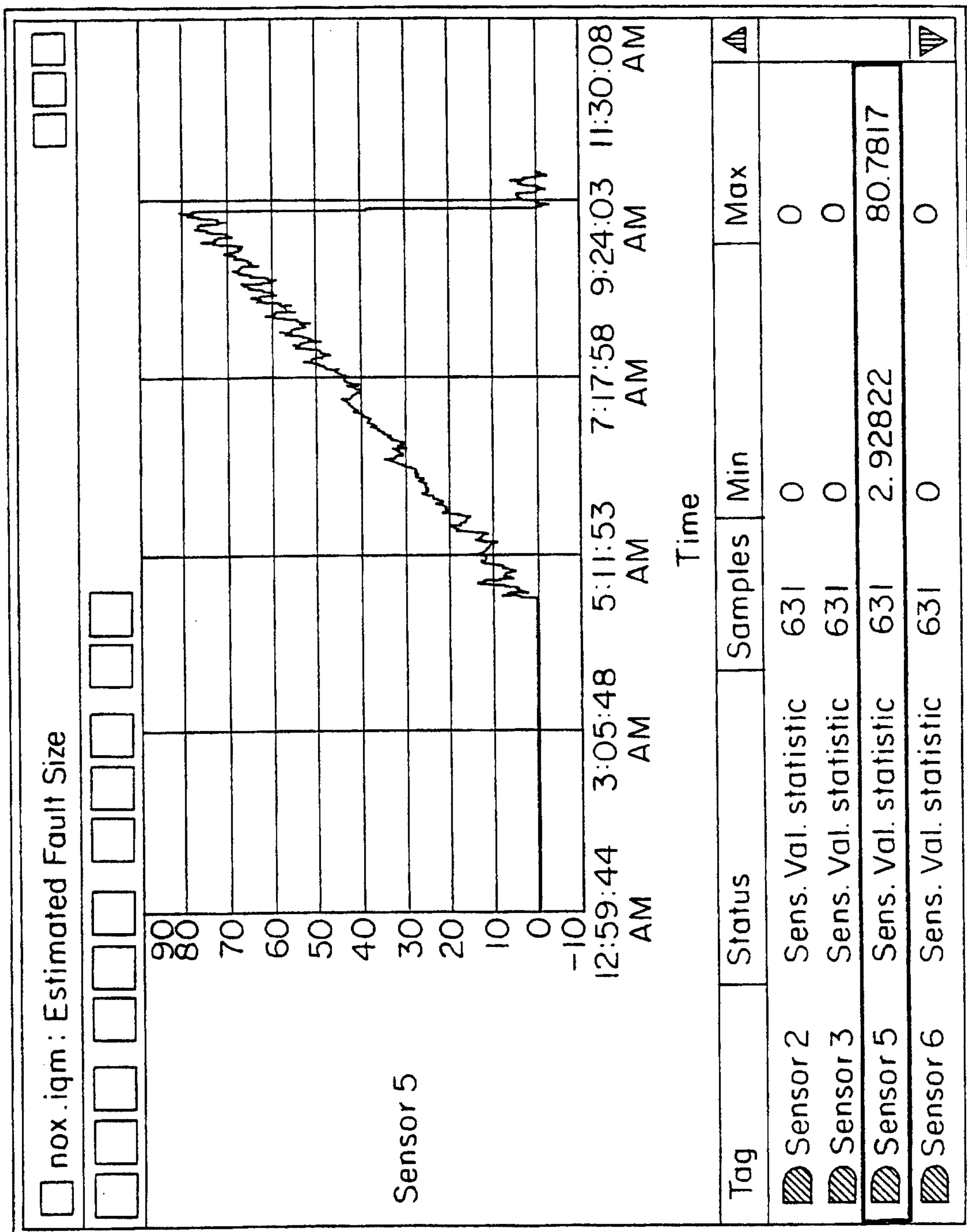
FIG. 5

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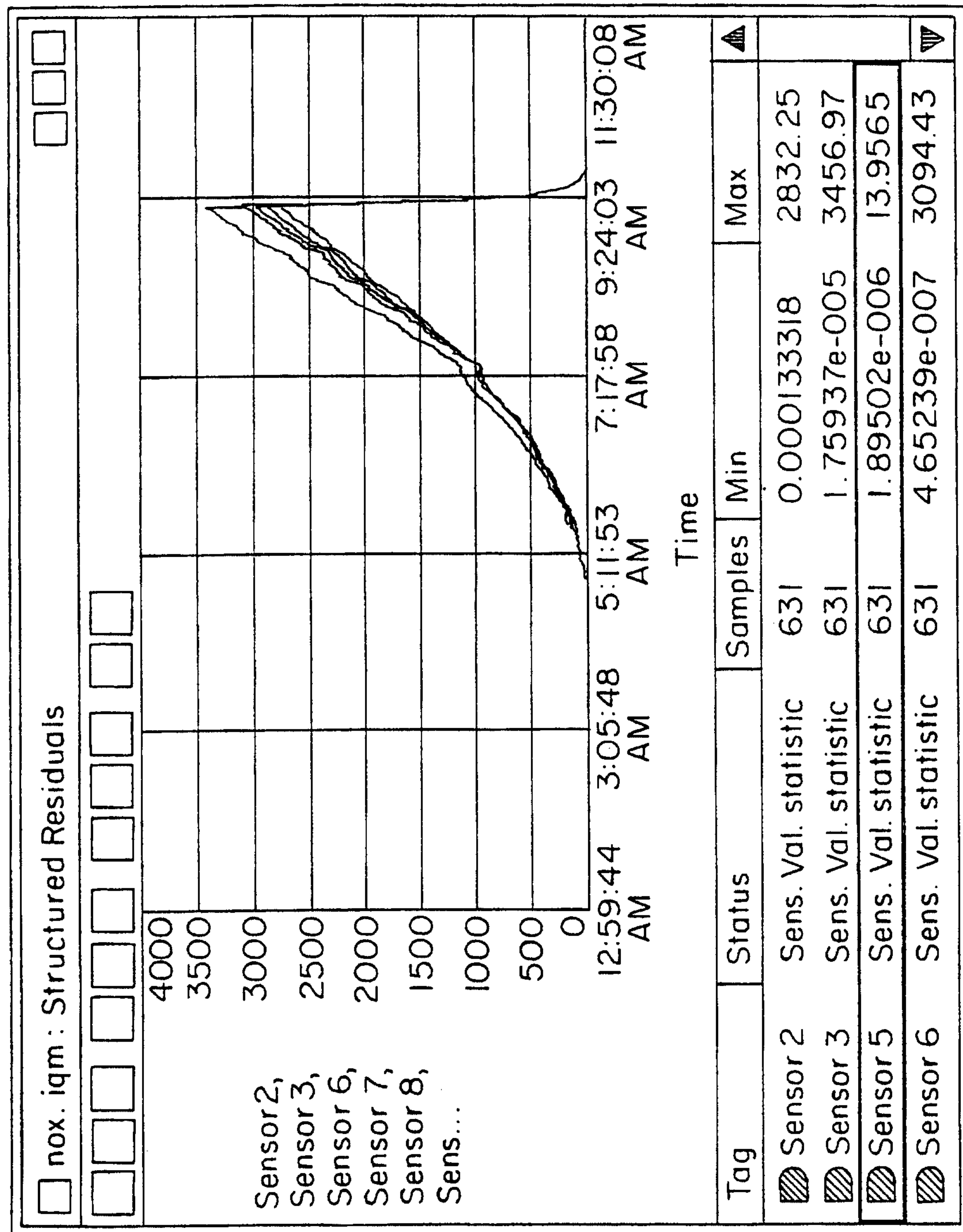
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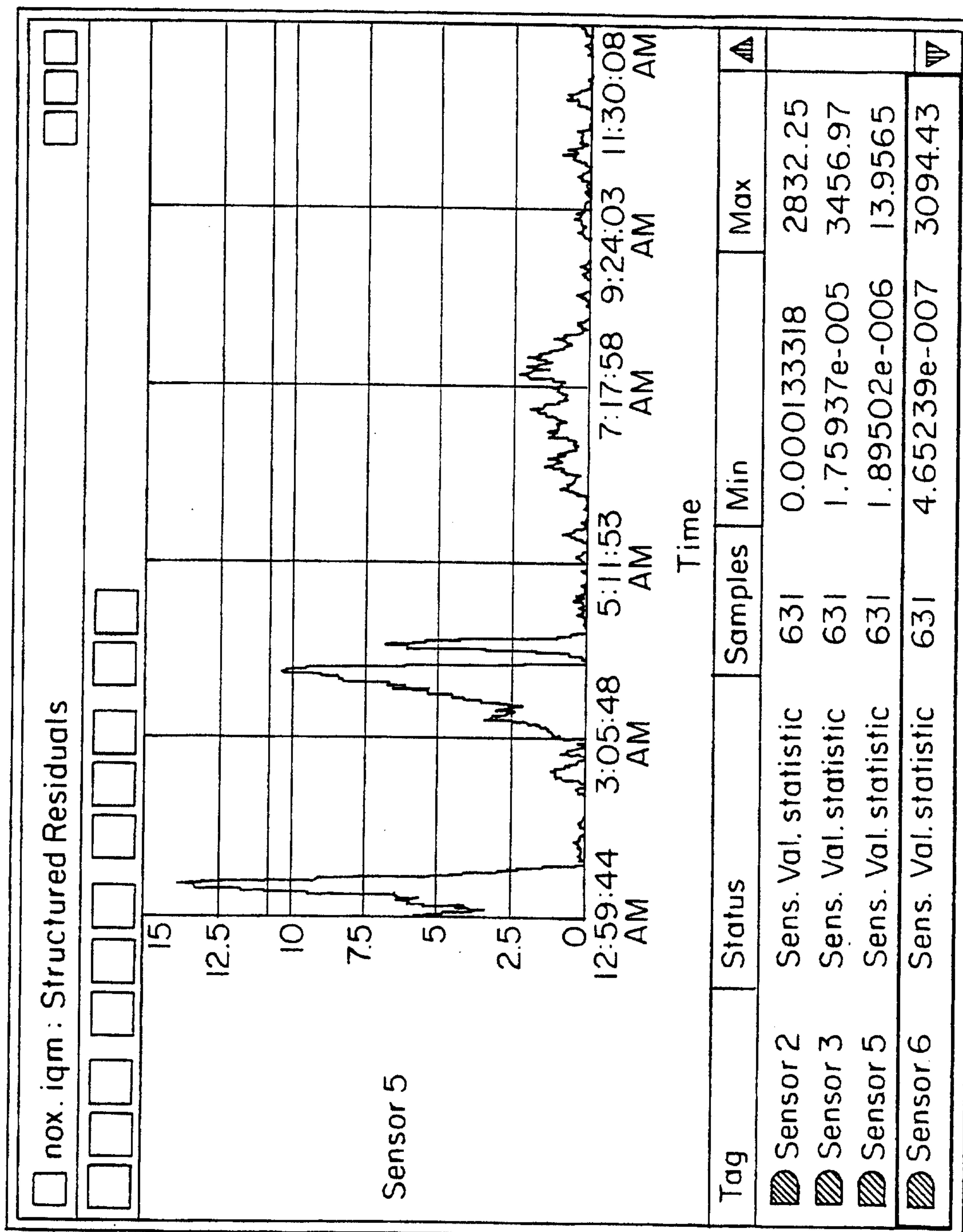
FIG. 6



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