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(54) Method and system for material degradation detection in an object by analyzing acoustic vibration data

(57) The invention claims a method and a system for material degradation detection in an object (11, 12) of said material by analyzing acoustic vibration data (VD) from said object (11, 12). The method comprises the following steps:
- training (100) a supervised learning machine (5) to recognize said acoustic vibration data (VD) without material degradation by extraction of at least one time-frequency feature (FF) of said acoustic vibration data (VD),
- detecting (101) said acoustic vibration data (VD) from said object (11),
- converting (102) said acoustic vibration data (VD) to a time-frequency domain representation (FR),
- extracting (105) at least one time-frequency feature (FF) of the time-frequency representation (FR) which is characteristic for said material degradation and
- detecting (106) by the learning machine (5) if the value of the extracted at least one time-frequency feature (FF) of the time-frequency domain representation (FR) is novel compared to the value of the time-frequency feature (FF) of the training.

The invention provides the advantage of robust material degradation detection under severe environmental conditions. With the method or system corrosion of downhole pipes can be detected exactly and robustly.

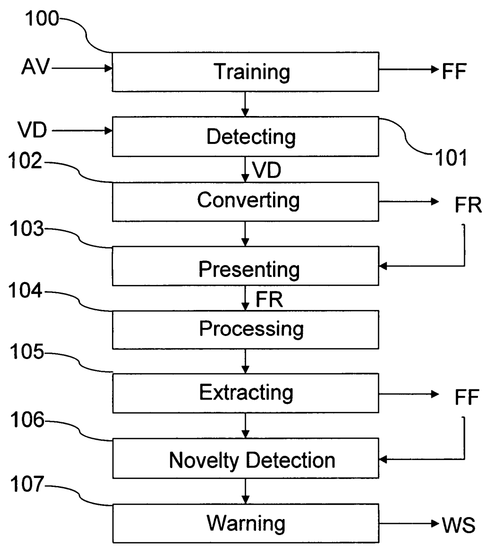

Fig. 9

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Description

Field of the Invention

[0001] The present invention relates to a method and a system for material degradation detection in an object by analyzing acoustic vibration data. Particularly, the invention is used to detect material degradation caused by corrosion in down-hole pipes.

Background of the Invention

[0002] Material degradation - in other words "material loss" -, particularly due to corrosion of the material, is a severe problem in many industry sectors. Corrosion means the disintegration of an engineered material into its constituent atoms due to chemical reactions with its surroundings. In the most common use of corrosion, it means electrochemical oxidation of metals in reaction with an oxidant such as oxygen. Formation of an oxide of iron due to oxidation of the iron atoms in solid solution is a well-known example of electrochemical corrosion, commonly known as rusting. This type of damage typically produces oxides or salts of the original metal. Corrosion can also occur in materials other than metals, such as ceramics or polymers, although in this context, the term degradation is more common. In other words, corrosion is the wearing away of material due to a chemical reaction.

[0003] Many structural alloys corrode merely from exposure to moisture in the air, but the process can be strongly affected by exposure to certain substances. Corrosion can be concentrated locally to form a pit or crack, or it can extend across a wide area more or less uniformly corroding the surface. Because corrosion is a diffusion controlled process, it occurs on exposed surfaces.

[0004] In the oil field industry material degradation plays a significant role. Particularly in down-hole oil pipes, corrosion damages in the pipe wall can cause severe disruptions. Therefore, it is important to detect corrosion at a very early stage. For detecting corrosion in pipes several solutions are known.

[0005] For example, the patent EP 1 097 290 B1 discloses a down-hole corrosion monitoring system comprising piezoelectric transducers, a microprocessor, an electrical power source and a conducting device, a control and instrumentation device and a display device. The transducers are arranged in a fixed array, spaced longitudinally and axially from each other and affixed to the section of a well casing or tubing to be monitored. The microprocessors are electrically connected to the transducers for activating the transducers, and for receiving and transmitting signals produced by the transducers. The monitoring system is used for monitoring a down-hole corrosion rate in an oil well tubing and casing strings in predicting its life and to avoid failures during operation. The system permits down-hole corrosion monitoring without taking the well out of service or disrupting the flow.

[0006] Another measurement setup is presented in the publication EP 1 467 060 A1 which discloses thin flexible piezoelectric transducers which are bonded to or imbedded into oilfield tubular members or structural members. The transducers are used to telemeter data as acoustic waves through the members. By proper spacing of transducers and phasing of driving signals, the transmitted signals can be directionally enhanced or encoded to improve transmission efficiency. The transducers may be used for health monitoring of the tubular or structural members to detect cracks, delaminations, or other defects. The flexible transducers are very thin so that overall dimensions of tubular or structural members are essentially unchanged by incorporation of the transducers.

[0007] It is the object of the present invention to provide a method and a system for improving detection of material degradation in objects, particularly for detecting corrosion in down-hole pipes.

Summary of the Invention

[0008] The above object and further benefits and advantages are realized by the independent claims. Further favorable embodiments are realized in the dependent claims.

[0009] The basic idea of the invention is to detect material degradation/material loss in objects autonomously by an analysis of material degradation correlates in evoked acoustic signals (acoustic vibration data), by a system which self-adjusts to the measurement conditions of the environment and by an energy efficient implementation. The objective is realized by a hybrid adapted signal processing learning machine. This hybrid learning machine extracts time-frequency features in the acoustic signals automatically such that these features are optimal for a subsequent novelty detection process. Optimal means that the feature extraction and the novelty detection process minimize the very objective function and thus form a hybrid union in the sense of mathematical optimization. In this way, the hybrid adapted signal processing learning machine auto-adapts to the acoustic signal on site such that it provides sensitive novelty detection, being at the same time very robust to any background noise of the environment.

[0010] For the self-calibration of the system a couple of data segments are derived from the object without material loss consecutively on short time-scales - short as compared to the time-scale of material loss. The hybrid novelty detection extracts the characteristic information from the data and becomes, up to large extent, invariant to background noise. However, this background noise lives on different time-scales than the rather slowly appearing changes due to material degradation in the signals, improving the robustness of said scheme further.

[0011] The invention comprises a hybrid adapted signal processing - supervised machine learning approach which "learns" the conditions on site, i.e. down-hole, after setting up the object, i.e. a pipe, and detects the material degradation correlates as represented by the extracted features as novel instances. As the actual physical conditions on site are unknown, such machine learning schemes represent a black-box model which complements the available (general) physical models of acoustic waves in materials. The a priori information from those general physical models defines only the physically reasonable range of appropriate features.

[0012] The energy efficiency is provided by sparsity regarding the activation, i.e. through actuators, and spatial sampling, i.e. by a number of sensors, by an efficient activation/excitation strategy, by a multirate/lattice implementation of signal processing, and by sparsity regarding information which has to be transferred to a central unit. Also the number of tests of the object can be adjusted to an estimated degradation rate using the hybrid learning machine, e.g., following the path of the features in the feature space. In the way, the number of tests for small degradation rates and thus the energy consumption can be reduced.

[0013] Novelty detection is the identification of new or unknown data or signals that a machine learning system is not aware of, during training. Novelty detection is a so-called one-class classification. The known data form one class and a novelty-detection method tries to identify outliers that differ from the distribution of ordinary data, which formed the single data class. Compared to multi-class classification, one-class classification is useful if outliers are sparse compared to ordinary data.

[0014] When dealing with complex multi-source signals with very limited a priori knowledge, such as the non-stationary acoustic response from an excited pipe downhole, a hybrid scheme offers a much higher degree of adaptivity. This is because not only the decision function of novelty detection process is optimized according to a learning rule but also the optimal features are fed to the novelty detection process. In this way, irrelevant information is directly removed, reducing the dimensionality of the problem and improving the novelty detection process.

[0015] The mathematical framework of such hybrid approaches with a uniform objective function is well known. Typically, the objective function is formulated using statistical learning theory combined with reproducing kernel Hilbert space regularization for binary classification. The advantages regarding the adaptivity and robustness of the hybrid approach with uniform objective function as compared to conventional two-stage schemes in which the feature extraction in the time-frequency domain is independent from the objective function of the learning machine, are well demonstrated. The adaptivity and robustness can especially be exploited in down-hole pipe applications as there is only very limited knowledge about the acoustic response signals and an adaptive self-calibration and robustness to noise is of major importance. The entire scheme can be implemented by a sparse kernel expansion for the novelty detection and a signal-adapted decomposition using the two-multiplier lattice, requiring a minimum number of floating point operations.

[0016] According to the present invention the above objective is fulfilled by a method for material degradation detection in an object of said material by analyzing acoustic vibration data derived from acoustic signals from said object, comprising:

- training a supervised learning machine to recognize said acoustic vibration data without material degradation by extraction of at least one time-frequency feature of said acoustic vibration data,
- detecting said acoustic vibration data from said object,
- converting said acoustic vibration data to a time-frequency domain representation,
- extracting at least one time-frequency feature of the time-frequency representation which is characteristic for said material degradation and
- detecting by the learning machine if the value of the extracted at least one time-frequency feature of the time-frequency domain representation is novel compared to the value of the time-frequency feature of the training.

[0017] The invention provides the advantage of robust and accurate material degradation detection under severe environmental conditions. As an example, the method is able to detect corrosion of down-hole pipes robustly.

[0018] According to a preferred embodiment the material degradation comprises thickness degradation and/or corrosion of said object.

[0019] Preferably, extracting uses a feature extraction procedure which auto-adapts to the acoustic vibration data on site in the sense that it extracts the time-frequency feature which is optimal for a machine learning procedure, i.e. the feature extraction follows the objective function of the learning machine.

[0020] Furthermore, the novelty detection scheme for detecting novel values of the time-frequency feature is embedded in statistical learning theory and whereas the extraction of the time-frequency feature is optimized for novelty detection using a (highly efficient) multirate signal processing strategy in the learning machine.

[0021] According to a preferred embodiment the object is excited by acoustic vibration at a first position and whereas said acoustic vibration data is detected at a second position in distance to the first position.

[0022] Preferably, the feature extraction maximises the distance between background acoustic noise and a response at the second position to the excitation at the first position.

[0023] Furthermore, the material of the object is plastic or metal. In a further embodiment the object is a pipe, particularly a down-hole pipe. Preferably, the first and second position are located on pipe segment connectors connecting pipe segments of the pipe.

[0024] Furthermore, the acoustic vibration excitation is auto-adapted to minimum energy consumption and optimal feature extraction properties. This means that the acoustic vibration excitation is optimized with respect to energy consumption and feature extraction properties.

[0025] In a further embodiment a warning signal is generated,

- if the value of the extracted at least one time-frequency feature of the time-frequency representation is novel compared to the value of the time-frequency feature of the training and
- if the value of the extracted at least one time-frequency feature of the time-frequency representation reaches a predefined critical value.

[0026] Preferably, the method comprises a quantification of the material degradation. Furthermore, the energy for excitation and detection is harvested from vibrations of the object. Finally, the excitation by acoustic vibration and the detection of the acoustic vibration data are executed only at predefined points in time.

[0027] According to the present invention the above objective is fulfilled by a system for material degradation detection in an object of said material by analyzing acoustic vibration data derived from acoustic signals from said object, comprising:

- a detection unit, which detects said acoustic vibration data from said object,
- a conversion unit, which converts said acoustic vibration data to a time-frequency domain representation,
- a processing unit, which processes said time-frequency representation, and which extracts at least one time-frequency feature of the time-frequency domains representation which is characteristic for said material degradation and
- a supervised learning machine, which detects if the value of the extracted at least one time-frequency feature of the time-frequency domain representation is novel compared to the value of the time-frequency feature of the acoustic vibration data without material degradation.

[0028] Preferably, the system is able to perform the methods according to the present invention.

Brief Description of the Drawings

[0029] More specialties and benefits of the present invention are explained in more detail by means of schematic drawings showing in:

Figure 1: an illustration of a tube segment with an excitation unit and a detection unit,
Figure 2: an illustration of a mode shape of a tube segment,
Figure 3: a diagram of detected steady state acoustic vibration data,
Figure 4: a diagram of time-frequency domain representations of acoustic vibration data of figure 3,
Figure 5: a diagram of two extracted time-frequency features restricted to a high frequency range,
Figure 6: a diagram of two extracted time-frequency features restricted to a medium frequency range,
Figure 7: a diagram of two extracted time-frequency features restricted to a low frequency range,
Figure 8: a block circuit diagram of a system for material degradation detection and
Figure 9: a flow chart of a method for material degradation detection.

Detailed Description of the Preferred Embodiments

[0030] Figure 1 shows an illustration of a typical pipe 13 segment of a pipe which can be used in a down-hole. The pipe segment 13 is equipped with an acoustic vibration excitation unit 2 at a first position P1. The excitation unit 2 can comprise a piezo actuator, preferably of a stack type. The excitation unit 2 is driven with a sinusoidally varying signal in the range of DC to 12 kHz. It produces an acoustic excitation in the radial direction of the pipe segment 13. At a second position P2 the pipe segment 13 is equipped with a detection unit 1 with a piezo accelerometer, i.e. preferably of a stack type. The radial direction of the pipe segment 13 is also the sensitive axis of the detection unit 1. In order to construct a long pipe many pipe segments 13 are jointed together by pipe segment connectors 14. Preferably, the excitation unit 2 and the detection unit 1 can be located at the position of the pipe segment connectors 14. Optionally, an excitation unit 2 can also function as a detection unit 1 and vice versa.

[0031] Figure 2 shows an illustration of an example of a standing wave pattern in the tube segment 13 of figure 1. After a certain transient period the excitation produces the standing wave pattern of which the shape (eigenmode) depends on the excitation frequency. As mentioned with figure 1 the detection unit 1 picks up the radial component of this vibration at their respective point of attachment. On the left side in figure 2 six modes in axial direction of the tube segment 13 can be seen. On the right side in figure 2 three nodes in circumferential direction are shown.

[0032] As the exact physical conditions on site are unknown, it is necessary to have non-stationary excitation patterns which give access to a wide range of physical settings. Depending on the excitation protocol, one can get non-stationary stead-state responses or transient responses. As the sensed pattern is non-stationary, these signals/vibration data are localized in time and scale/frequency. Scales are frequency bands. The centers of these frequency bands can be associated with an inversely related frequency. In other words, a time-scale analysis can be associated with a time-frequency analysis. In order to simplify, associated frequency representations are used in the following.

[0033] For demonstration of the functionality of the invented method and system a lab scale experiment with three different pipe segments are used. The wall thickness of the pipe segments are decreasing. The decreasing wall thickness represents a physical model for wall-thickness degradation due to corrosion.

[0034] Figure 3 shows a diagram of the steady state responses/acoustic vibration data from three different pipe segments, with decreasing wall thickness from top to down (7,1 mm, 5,6 mm, 4,0 mm). These sampled signals are considered as vectors in the original data space $S \subset R^d$. The x-axes shows the time in μs and the y-axis the power level of the detected signal. The acoustic vibration data are converted to time-frequency domain representations. Figure 4 shows a diagram of the time-frequency domain representations of figure 3. The x-axis shows the time in s and the y-axis the frequency in kHz. The grey level is proportional to the power level.

[0035] Given the physical a-priori knowledge, such time-frequency energy distributions provide a valid domain for the feature extraction. In a nutshell, the invention will just provide automatically a solution to different problems (in the sense of statistical learning and using the physical a priori knowledge):

- how can the best (in the sense of stable/characteristic/discriminative) features be extracted from such time-frequency domain representations and
- how can they be robustly used for material degradation detection, i.e. corrosion.

[0036] To solve these problems, a hybrid theory is chosen. The used feature extraction provides automatically a low dimensional vector of characteristic and physically reasonable features FF. The dimension of this feature space $F \subset R^n$ is much smaller than the dimension of the data space S, i.e., n << d Typical values are n = 6 versus d = 250 000 for the signals considered here. This is called "dimensionality reduction" and is a well known concept in pattern recognition.

[0037] The features FF are extracted by optimized basis functions in a hybrid learning theory. The entire signal/data processing is based on multirate signal processing and can be implemented by two-multiplier lattice, the most efficient implementation of filter banks. Filters of a minimum order N=5 provide already enough flexibility here. The learning system g of a learning machine is automatically adjusted by providing a number of M patterns as represented by the features $f_i \in F$ (i = 1, ..., M) in the case of pure novelty detection (= "one class classification"). Afterwards it implements a map g : $F \rightarrow$ {no material degradation; material degradation}. This is called "kernel based" novelty detection.

[0038] Alternatively, one can also provide a set of associations which discriminate the signal from the background noise ("kernel based hyperplane classification"). It is possible to easily get patterns of the pure background noise by sensing the signal/vibration data without excitation.

[0039] Figures 5 to 7 show diagrams of the tight decision boundary in *F*. This decision boundary is a back-projection from the very high dimensional induced feature space of kernel learning machines in which the decision boundary is just a sphere. Figures 5 to 7 just show the tight decision boundary L (points touch the line) as no impact of background noise was present in the lab setup. A number of 15 repeated measurements with very same settings in three different pipe segments with three different wall thicknesses are represented by only two time-frequency features FF (feature 1, feature 2). The values of feature 1 are drawn on the x-axis and the values of feature 2 are drawn on the y-axis. A thick wall is a model for non corrosion, a slightly thinner wall is a model for mid-corrosion and a thin wall is a model for corrosion.

[0040] The time-frequency features FF (feature 1, feature 2) are extracted automatically and the learning machine is automatically adjusted from a few measurements. It is noticeable, that the two time-frequency features FF for the repeated measurements in the non material degraded pipe segment are well clustered (boundary L). The data for the material degraded pipe segments (mid-corroded, corroded) are projected to a different domain D, making the novelty/corrosion detection easy.

[0041] Figure 8 shows a block circuit diagram of a system used for material degradation detection of an object 11. The system comprises a vibration excitation unit 2 with a piezoelectric stack 8 which excites acoustic vibration in the object 11. The acoustic vibration is detected by a further piezoelectric stack 8 of a detection unit 1. The detection unit 1 is located in distance to the vibration excitation unit 2. The detection unit 1 detects acoustic vibration data which are converted to a time-frequency domain representation by a conversion unit 3. The conversion unit 3 is connected to a processing unit 4 which processes the time-frequency domain representation and extracts time-frequency features of the time-frequency domain representation. Only such time-frequency features are extracted which are symptomatic for material degradation.

[0042] Via a wireless transmission unit 9 the values of the extracted time-frequency features are transmitted to a supervised learning machine 5. The learning machine 5 detects if the values of the extracted time-frequency features of the time-frequency domain representation are novel compared to the values of the time-frequency feature of the acoustic vibration data without material degradation. The values without material degradation are determined during a training phase where the object is not degraded. Optionally, a wired transmission can be used.

[0043] The learning machine 5 is connected to a warning signal unit 10. If the values of the extracted time-frequency features of the time-frequency domain representation are novel compared to the values of the time-frequency features without material degradation and if the values of the extracted time-frequency features of the time-frequency representation reach a predefined critical value, the warning signal unit 10 generates a warning signal WS. The learning machine 5 is connected to a classification and/or regression machine 6 which in addition quantifies the material degradation.

[0044] In a preferred embodiment the detection unit, the conversion unit and the processing unit are arranged at the object and the learning machine is arranged in a distant location. In a further embodiment the learning machine comprises a novelty detection scheme for detecting novel values of the time-frequency feature which is embedded in statistical learning theory. In a further embodiment of the system according to the present invention the feature extraction is optimized for novelty detection using a highly efficient multirate signal processing strategy in the learning machine.

[0045] In a preferred embodiment the object is excited by an acoustic vibration excitation unit at a first position and the detection unit is placed at a second position in distance to the first position. In one embodiment the object is made of plastic or metal. In a further embodiment the object is a sheet or a cylindrical body. In a further embodiment the detection unit and/or the acoustic vibration excitation unit are located on pipe segment connectors connecting pipe segments of a pipe.

[0046] Figure 9 shows a flow chart of a method for material degradation detection in an object. In a first step 100 a supervised learning machine is trained to recognize acoustic vibration data VD without material degradation by extraction of time-frequency features FF of the detected acoustic vibration data VD. In order to get acoustic vibration data VD the object is excited with acoustic vibrations AV. In a second step 101 - after the training phase - further acoustic vibration data VD from the object are detected. In step 102 the acoustic vibration data VD are converted to a time-frequency domain representation FR, i.e. using wavelet transformation.

[0047] In the next step 103 the time-frequency domain representation FR is presented to the learning machine, alternatively to a processing unit. In step 104 the time-frequency domain representation FR is processed by the learning machine or the processing unit. In the next step 105 time-frequency features FF of the time-frequency domain representation FR which are significant for the material degradation are extracted by the learning machine or the processing unit.

[0048] In a further step 106 it is detected whether the values of the extracted time-frequency features FF of the time-frequency domain representation FR are novel compared to the values of the time-frequency features FF of the training phase. In the last step 107 a warning signal WS is generated if the values of the extracted time-frequency features FF of the time-frequency domain representation FR are novel compared to the values of the time-frequency features FF of the training and if the values of the extracted time-frequency feature FF (or at least of one time-frequency feature FF) of the time-frequency domain representation FR reached a predefined critical value.

[0049] It is apparent that various changes can be made in the systems and the methods disclosed herein, without departing from the scope of the invention as defined by the appended claims. For example, the invention can also be used for a measurement of thickness degradation in metal sheets or similar geometric objects.

Reference Signs

[0050]

1	Detection unit
2	Acoustic vibration excitation unit
3	Conversion unit
4	Processing unit
5	Supervised learning machine
6	Classification and/or regression machine
7	Harvesting unit
8	Piezoelectric stack
9	Transmission unit
10	Warning signal unit
11	Object
12	Pipe
13	Pipe segment
14	Pipe segment connector
100	Training a supervised learning machine 5
101	Detecting acoustic vibration data VD
102	Converting the acoustic vibration data VD
103	Presenting the time-frequency representation FR
104	Processing the time-frequency representation FR
105	Extracting a time-frequency feature FF
106	Novelty detection
107	Generating a warning signal WS
AV	Excited acoustic vibration
D	Different domain of time-frequency feature FF
f	frequency
FF	Time-frequency feature
FR	Time-frequency representation
L	Boundary line
P1	First position
P2	Second position
t	time
VD	Acoustic vibration data
WS	Warning signal

Claims

1. A method for material degradation detection in an object (11, 12) of said material by analyzing acoustic vibration data (VD) from said object (11, 12), comprising:

- training (100) a supervised learning machine (5) to recognize said acoustic vibration data (VD) without material degradation by extraction of at least one time-frequency feature (FF) of said acoustic vibration data (VD),
- detecting (101) said acoustic vibration data (VD) from said object (11, 12),
- converting (102) said acoustic vibration data (VD) to a time-frequency domain representation (FR),
- extracting (105) at least one time-frequency feature (FF) of the time-frequency domain representation (FR) which is characteristic for said material degradation and
- detecting (106) by the learning machine (5) if the value of the extracted at least one time-frequency feature (FF) of the time-frequency domain representation (FR) is novel compared to the value of the time-frequency feature (FF) of the training.

2. The method as claimed in claim 1, whereas material degradation comprises a thickness degradation and/or a corrosion of said object (11, 12).

3. The method as claimed in claim 1 or 2, whereas extracting (105) uses a feature extraction procedure which auto-adapts to the acoustic vibration data (VD) on site in the sense that it extracts the time-frequency feature (FF) which is optimal for a machine learning procedure.

4. The method of any of previous claims, whereas the novelty detection scheme for detecting (106) novel values of the time-frequency feature (FF) is embedded in statistical learning theory and whereas the extraction (105) of the time-frequency feature (FF) is optimized for novelty detection using a multirate signal processing strategy in the learning machine (5).

5. The method of any of previous claims, whereas said object (11, 12) is excited by acoustic vibration (AV) at a first position (P1) and whereas said acoustic vibration data (VD) is detected at a second position (P2) in distance to the first position (P1).

6. The method of claim 5, whereas the feature extraction (105) maximises the distance between background acoustic noise and a response at the second position (P2).

7. The method of any of previous claims, whereas the material said object (11, 12) is made of is plastic or metal.

8. The method of any of previous claims, whereas said object (11) is a pipe (12), particularly a down-hole pipe.

9. The method of claim 8 and any of claims 5 to 7, whereas the first and second position (P1, P2) are located on pipe segment connectors (14) connecting pipe segments (13) of the pipe (12).

10. The method of any of claims 5 to 9, whereas the acoustic vibration excitation is optimized with respect to energy consumption and feature extraction properties.

11. The method of any of previous claims, whereas

- if the value of the extracted at least one time-frequency feature (FF) of the time-frequency domain representation (FR) is novel compared to the value of the time-frequency feature (FF) of the training and
- if the value of the extracted at least one time-frequency feature (FF) of the time-frequency domain representation (FR) reaches a predefined critical value,
- a warning signal (WS) is generated (107).

12. The method of any of previous claims, with a quantification of the material degradation.

13. The method of any of claims 5 to 12, whereas energy for excitation and detection is harvested from vibrations of the object (11, 12).

14. The method of any of claims 5 to 13, whereas the excitation by acoustic vibration and the detection (101) of the acoustic vibration data (VD) are executed only at predefined points in time.

15. A system for material degradation detection in an object (11, 12) of said material by analyzing acoustic vibration data (VD) from said object (11, 12), comprising:

- a detection unit (1), which detects said acoustic vibration data (VD) from said object (11, 12),
- a conversion unit (3), which converts said acoustic vibration data (VD) to a time-frequency domain representation (FR),
- a processing unit (4), which processes said time-frequency representation (FR), and which extracts at least one time-frequency feature (FF) of the time-frequency domain representation (FR) which is characteristic for said material degradation and
- a supervised learning machine (5), which detects if the value of the extracted at least one time-frequency feature (FF) of the time-frequen-

cy domain representation (FR) is novel compared to the value of the time-frequency feature (FF) of the acoustic vibration data (VD) without material degradation.

16. The system of claim 15 performing a method according to any of claims 1 to 14.

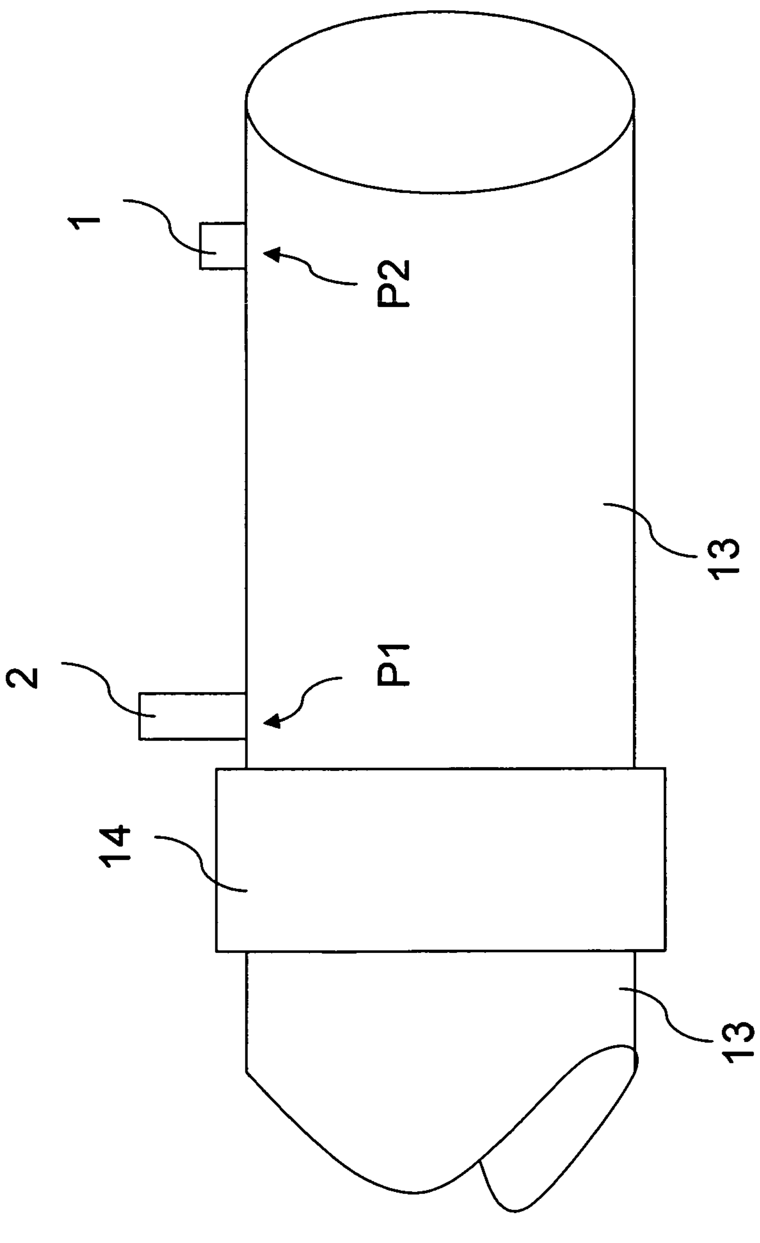

Fig. 1

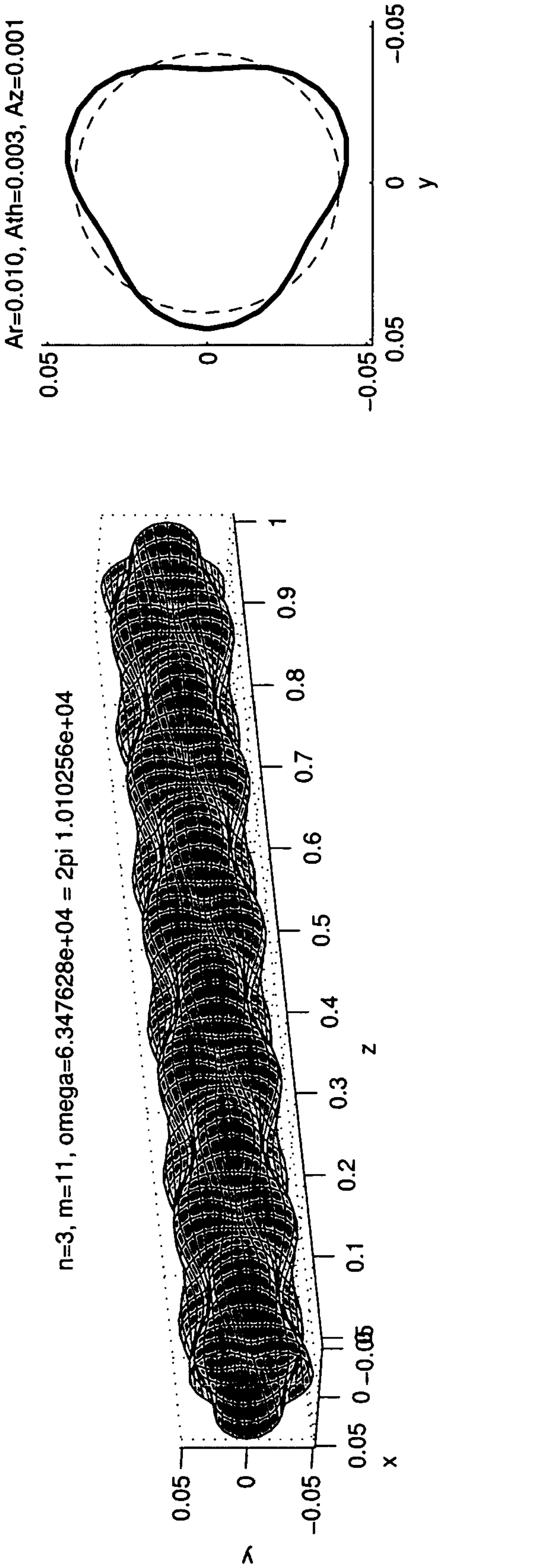
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Fig. 2

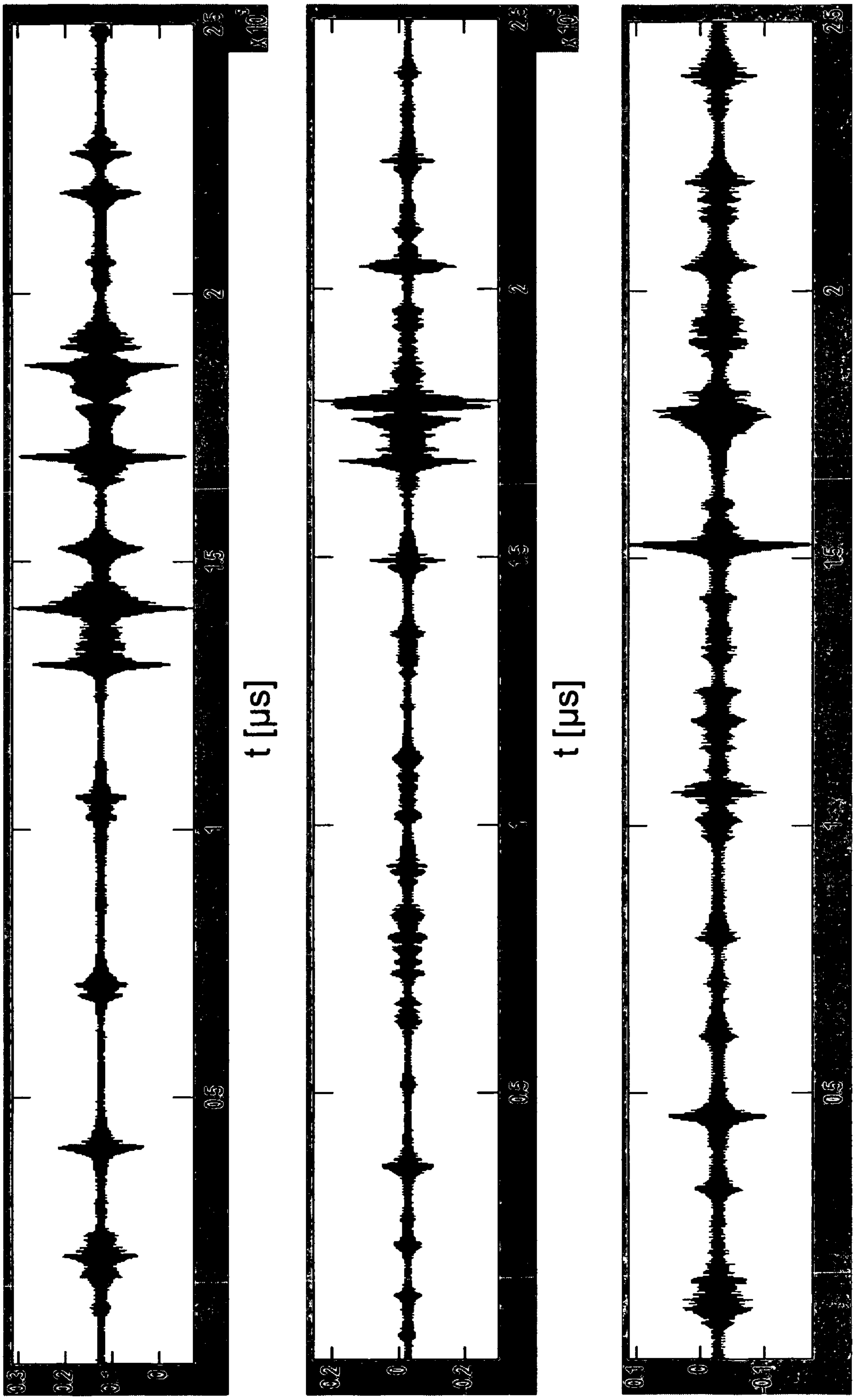

Fig. 3

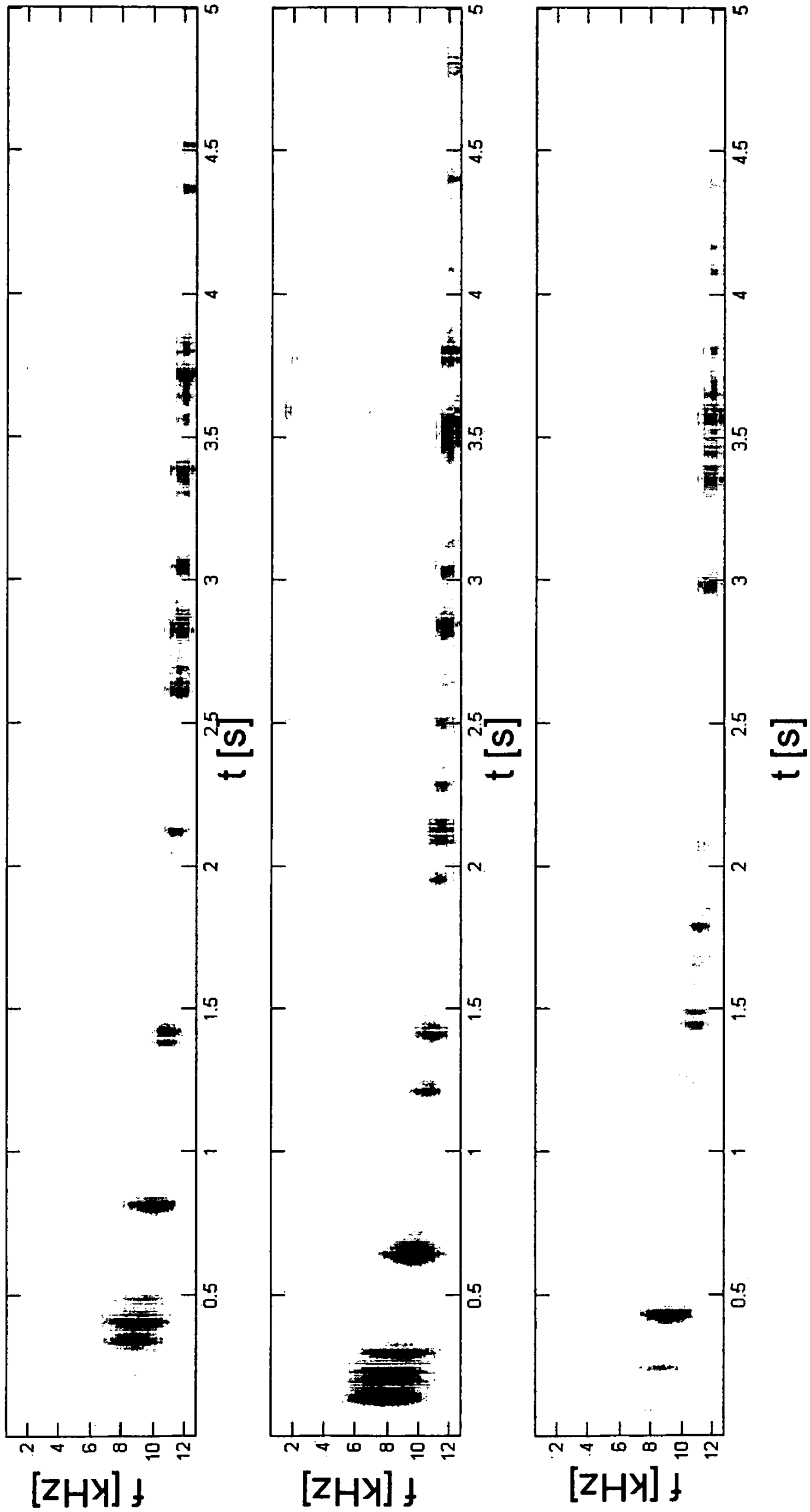

Fig. 4

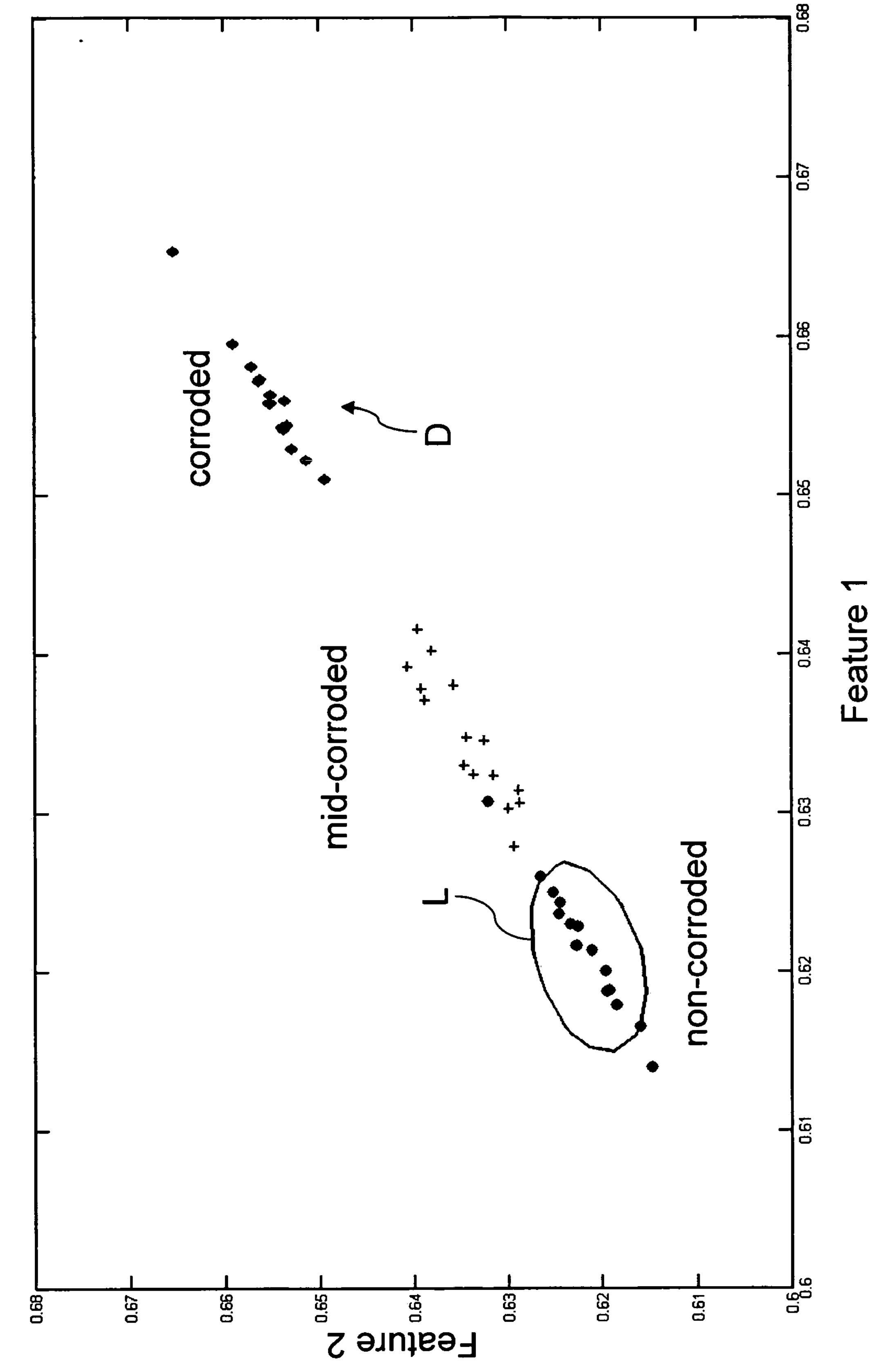
corroded
mid-corroded
non-corroded
D
L
Feature 1
Feature 2
0.6
0.61
0.62
0.63
0.64
0.65
0.66
0.67
0.68

Fig. 5

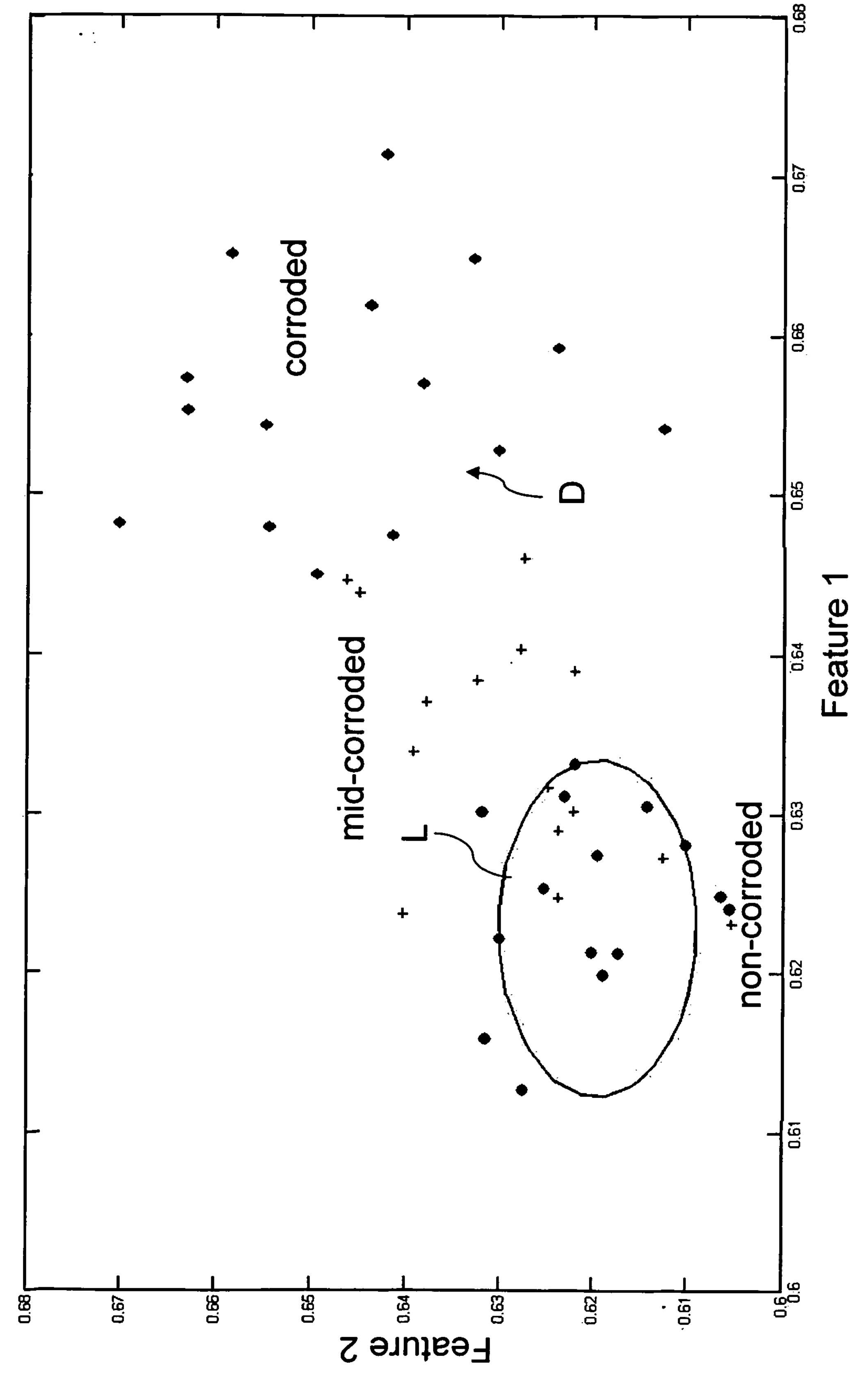
corroded
mid-corroded
non-corroded
D
L
Feature 1
Feature 2
0.6
0.61
0.62
0.63
0.64
0.65
0.66
0.67
0.68

Fig. 6

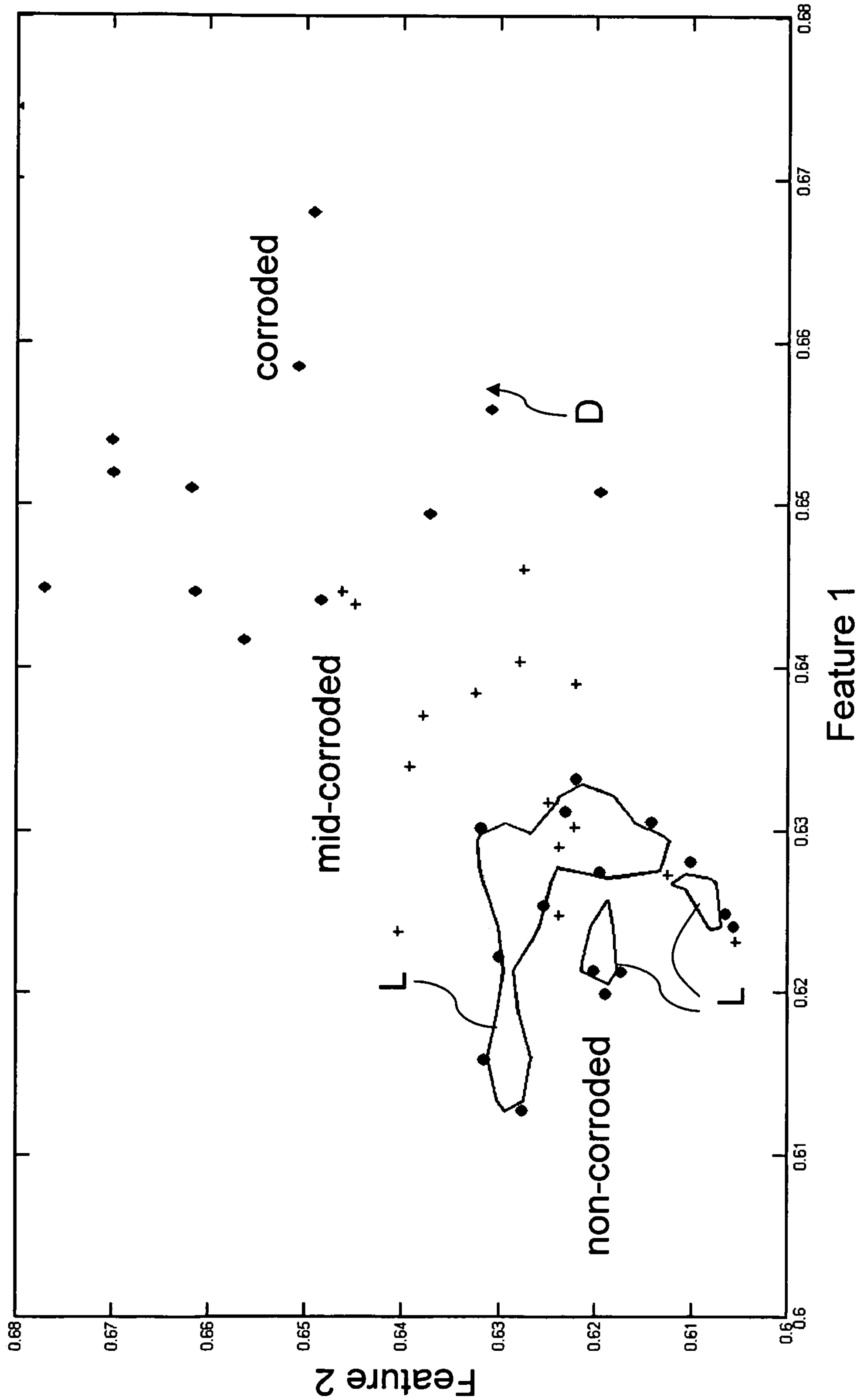
Feature 2
Feature 1
0.6
0.61
0.62
0.63
0.64
0.65
0.66
0.67
0.68
corroded
mid-corroded
non-corroded
D
L
L

Fig. 7

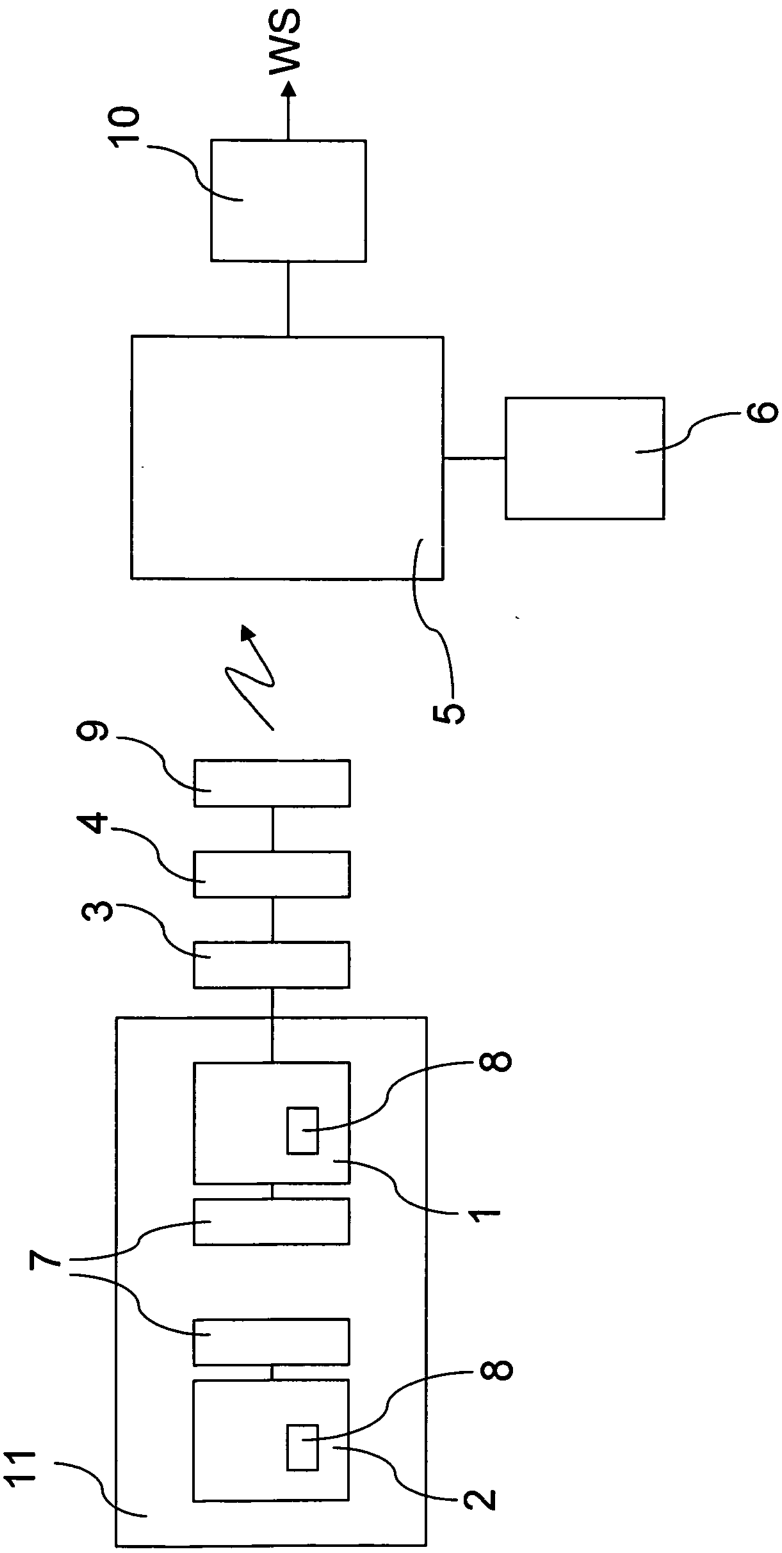

Fig. 8

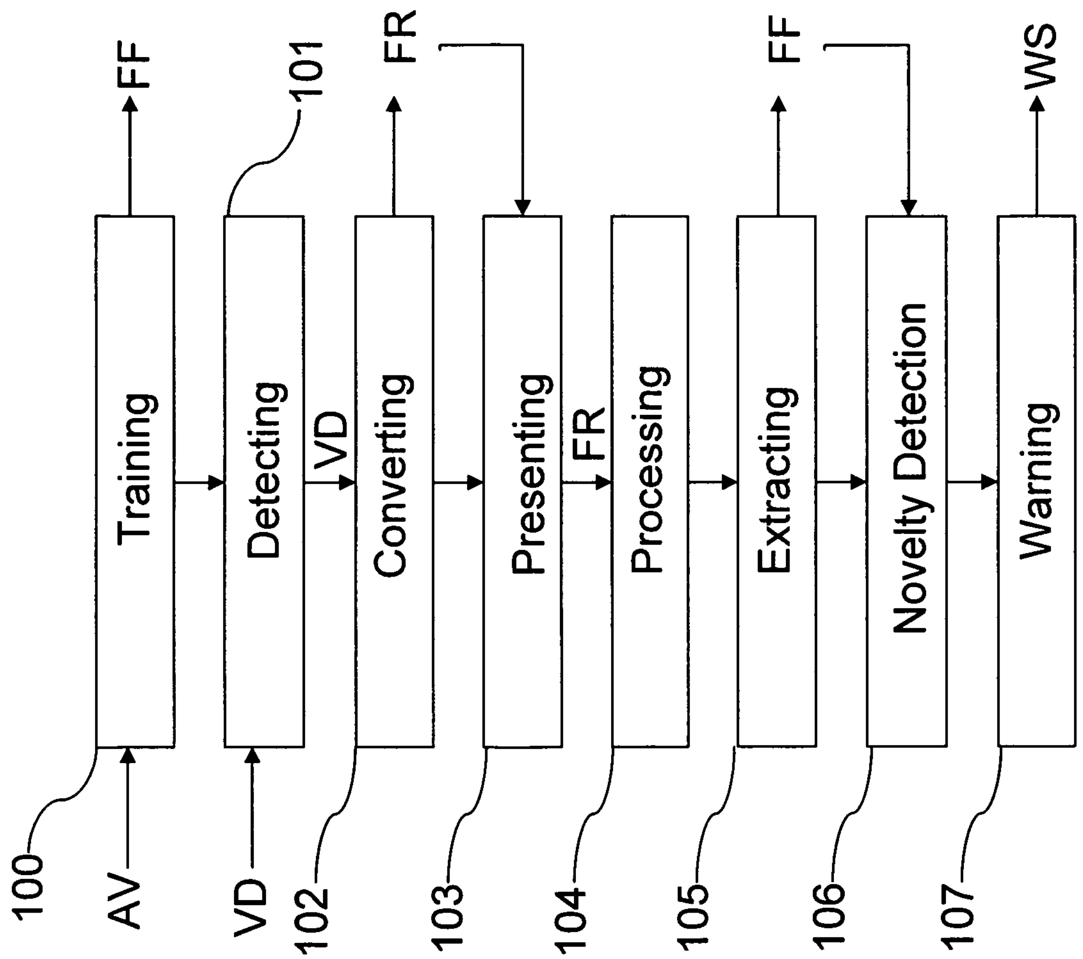
Training
Detecting
Converting
Presenting
Processing
Extracting
Novelty Detection
Warning
AV
VD
FF
101
FR
FF
WS
100
102
103
104
105
106
107

Fig. 9

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EUROPEAN SEARCH REPORT

Application Number
EP 12 00 0950

DOCUMENTS CONSIDERED TO BE RELEVANT

Category	Citation of document with indication, where appropriate, of relevant passages	Relevant to claim	CLASSIFICATION OF THE APPLICATION (IPC)
X	GERT VAN DIJCK ET AL: "Information Theory Filters for Wavelet Packet Coefficient Selection with Application to Corrosion Type Identification from Acoustic Emission Signals", SENSORS, vol. 11, no. 6, 27 May 2011 (2011-05-27), pages 5695-5715, XP55032996, DOI: 10.3390/s110605695 * figures 1,2,9 * -----	1-16	INV. E21B47/00
X	Dino Isa ET AL: "Pipeline defect detection using support vector machines", 6th WSEAS International Conference on CIRCUITS, SYSTEMS, ELECTRONICS,CONTROL & SIGNAL PROCESSING, 29 December 2007 (2007-12-29), pages 162-168, XP55032994, Cairo, Egypt Retrieved from the Internet: URL:http://www.wseas.us/e-library/conferences/2007egypt/papers/568-369.pdf [retrieved on 2012-07-17] * figures 5,6; tables 1,2 * -----	1-16	TECHNICAL FIELDS SEARCHED (IPC): E21B
A	US 4 893 286 A (COBB WESLEY N [US]) 9 January 1990 (1990-01-09) * column 6, line 1 - line 44; figures 11-14 * * column 28, line 25 - column 29, line 59 * -----	1-16	

The present search report has been drawn up for all claims

1

Place of search	Date of completion of the search	Examiner
The Hague	18 July 2012	Dantinne, Patrick

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18-07-2012

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US 4893286 A	09-01-1990	NONE	

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