

**Method for characterizing the coherence of an
environment characteristic measurements**

The present invention relates to a method of
5 characterizing the coherence of measurements of
characteristics of a medium and, more particularly, of
logging data, the said method making it possible, in
particular, to characterize the relationships between,
10 on the one hand, a qualitative variable whose origin is
not logging-related and, on the other hand, logging
measurements.

An oil field may, for example, comprise a number of
wells which may be close together or far apart.

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When studying such a field, geologists generally have
available only a small number of core samples taken
from one or more wells, which are then considered as
being reference wells, the various measurements made on
20 the said core samples being considered as being
reference measurements. On zones containing wells which
are referred to as application wells and from which no
core sample has been taken, specialists use other means
for studying them, such as logging, seismic, etc. The
25 data provided by these other means make it possible to
determine petro-physical or other parameters and, in
particular, to check their coherence with the
measurements made on the available core samples.
Checking and/or extrapolating data which are not
30 related to core samples make it possible to
characterize both quantitative variables and
qualitative variables.

A geologist or another specialist, such as a
35 sedimentologist, divides the zone from which core
samples are available into a certain number of slices
representative of various qualitative variables such as
facies, sedimentary body, sedimentary environment, etc.
Each of these variables is generally assigned a number.

For example, clay facies is referenced by the number 1, sand facies by the number 2, sandstone facies by the number 3, and so on. In this way, a qualitative variable is obtained which is referenced in depth and contains whole values, each value corresponding to one class of one logging viewpoint.

It should be noted that the measurements or descriptions on core samples may greatly exceed the resolution of conventional logging tools as used currently and, in particular, by the company SCHLUMBERGER. However, these descriptions are sometimes visual, and therefore subjective because they depend directly on the quality of observation by the geologist or the sedimentologist. It is not easy to obtain a comparison or a parallel between logging measurements made on one or more application wells because numerous "mixing" zones are often observed, that is to say the logging measurements may belong to several classes.

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In order to reduce the specialist's subjectivity as far as possible, the use of statistical or neural classification methods has been advocated. Conventional statistical methods, such as those developed by TETZLAFF et al. at SPWLA in 1989, JIAN et al. in "Journal of Petroleum Geology, V. 17, January, p. 71-88, or GREDER et al. at SPWLA in 1995, give poor results when the classes overlap too much, because these so-called parametric methods assume that each class follows a Gaussian law. However, the shape of a class is generally more complex than a simple Gauss curve.

Neural classification methods, described in particular by CARDON et al. in 1991, ROGERS et al. in AAPG Bulletin 1992, V. 76, No. 5 p. 38-49, HALL et al. at SPWLA in 1995 or MOHAGHEGH in 1995 and 1996, also give poor results owing to the fact that the said methods are highly sensitive to incoherences observed in the

measurements. In neural networks whose learning is supervised, the network learns to recognize one shape from examples. However, a logging measurement may be attributed to one class in a first step, then be
5 attributed to another class in another step. Neural networks with overlaid levels do not succeed in recognising that a single measurement is involved.

Reference was made above to core samples which are
10 taken from one or more reference wells and on the basis of which classifications have been made using the methods summarized above. It should, however, be noted that the said methods have also been applied to logging measurements produced directly in one reference well or
15 several reference wells, for which the said logging measurements have been considered as satisfactory because of their accuracy or since they were representative of qualitative variables of the said well or wells. It is nonetheless true that the results
20 obtained with the said methods on reference logging measurements were unsatisfactory and suffered from the same drawbacks. Specifically, these methods give poor results when a facies not described in the learning set is encountered in an application well and/or when the
25 quality of the logging measurements is compromised by defective calibration or corrections, or on account of poor acquisition conditions.

The object of the present invention is to overcome the
30 aforementioned drawbacks and to provide a method of characterizing the coherence of logging data which is not parametric and which permits objective evaluation of the representativeness of a learning set, formed from logging data, in application sets which are formed by
35 logging data to be identified, by picking out the depth intervals over which a problem is detected. Indeed, the method according to the present invention does not require the knowledge of any a priori probabilistic model by virtue of the fact that each domain in the

learning set is determined by k nearest neighbours searching.

The method of characterizing the coherence of measurements made in a given medium, is of the type consisting in:

- taking N types of reference measurements at each point (P_i) of a given reference set of the said medium, each point (P_i) being defined by a depth dimension, the group of N measurements which are associated with each point (P_i) constituting a reference observation (X_i),
 - forming at least one N -dimensional learning set containing all the said points (P_i),
 - taking at least N application measurements at each point (Q_i) of an application set of the said medium, which is different from the said reference set, each group of application measurements which are associated with the said point (Q_i) constituting an application observation (x_i),
 - comparing each application observation (x) with all the reference observations (X_i) of the said learning set,
- characterized in that it furthermore consists in:
- constructing a neighbourhood domain (D_i) for each reference observation (X_i) of the learning step using the k nearest neighbours process (K-NN), the said neighbourhood domains constituting the said learning set which defines an acceptance class (C_a) for application observations (x) in the application set,
 - defining a degree of membership of the application observations (x) to the said acceptance class (C_a), each application observation (x) being assigned to the acceptance class (C_a) when its membership degree is at least greater than a first threshold (S_1).

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According to another characteristic of the invention, each application observation (x) is assigned to one of three classes consisting of the acceptance class (C_a), an ambiguity class (C_o) or a reject class (C_d).

According to another characteristic of the invention, the membership degree comprises at least two thresholds (S_1, S_2), the second threshold being less than the first threshold (S_1).

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According to another characteristic of the invention, an application datum (x) is assigned to the reject class (C_d) when its membership degree is less than the said second threshold (S_2).

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According to another characteristic of the invention, an application datum (x) is assigned to the ambiguity class when its membership degree lies between S_1 and S_2 .

15 According to another characteristic of the invention, the membership degree is defined by the membership function:

$$\mu_i(x) = e^{\left[\frac{x - X_i}{\sigma_i} \right]} \quad (1)$$

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in which

X_i is an observation in the learning set, i lying between 1 and n_a ,

n_a corresponds to the number of reference observations in the learning set,

25 σ_i is the radius of the domain centred on the observation X_i ,

x is an application observation in the application set.

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According to another characteristic of the invention, in order to clarify an ambiguity attached to an application observation (x), an $(n-1)$ -dimensional learning set is constructed, the dimension removed

35 corresponding to one type of measurements.

According to another characteristic of the invention, the membership degree $\mu(x)$ corresponds to the mean of

the k' strongest memberships $\mu_i(x)$ to the domains D_i in the learning set.

According to another characteristic of the invention,
5 the mean k' lies between 1 and k .

According to another characteristic of the invention,
the value of k' is very much greater than 1.

10 Other advantages and characteristics of the present invention will become more clearly apparent on reading the method, as well as the appended drawings in which:

- Figure 1 is a schematic representation of the
15 acceptance (C_a), ambiguity (C_o) and reject (C_d) classes which are used in the method according to the present invention;

- Figure 2 is a synthetic representation in logarithmic form of the degrees of threshold similarity (ST) and
20 similarity degree (MD) ;

- Figure 3 is a schematic representation of the neighbourhood domains D_i of the learning set as constructed according to the method of the present invention;

25 - Figures 4A to 4C are logging representations for a well A;

- Figures 5A to 5C are logging representations for a well B;

- Figures 6A to 6D are cross plots of a learning set
30 and acceptance (C_a), ambiguity (C_o) and reject (C_d) relating to well A;

- Figures 7A to 7D are diagrams similar to those in Figures 6A to 6D but with removal of one type of measurement, in this case RHOB;

35 - Figures 8A to 8D are cross plots of a learning set and acceptance (C_a), ambiguity (C_o) and reject (C_d) relating to well B;

- Figures 9A to 9D are diagrams similar to those of Figures 8A to 8D but whose co-ordinates are ILD and DT.

In a given medium, for example an oil field, N separate preliminary measurements are taken or made, each corresponding to one of the physical characteristics of the subsurface of the medium. The nature of the preliminary measurements is arbitrary. They may be statistical measurements made using specific tools or with the aid of suitable methods. They may also be measurements made on one or more core samples taken from one or more wells in the said oil field, or alternatively logging measurements made in one or more boreholes. In all cases, these preliminary measurements constitute reference measurements according to the invention. The part of the medium in which the preliminary measurements are made defines the reference set.

In the same way, the measurements which are made in another part of the medium, separate from the previous one, are considered in the present invention as being application measurements which will be compared with the reference measurements. The part of the said medium in which these application measurements are made defines an application set which may consist of one or more other wells in the oil field.

In the rest of the description, and by way of example, the reference measurements are logs which are representative of a particular lithology observed in the reference set, in particular in one or more boreholes in the said reference set.

The logs are used for forming a learning set, and the lithology example in question comprises the following facies: sandstone, silt, and cemented sandstone with traces of argillaceous sandstone and clay. The logs used are, in particular, those known by the references RHOB for measuring density, VSH for clay indication, DT for measuring the propagation speed of the waves in the

medium and ILD for measuring the deep resistivity. Clearly, the number of logs may be increased or decreased.

- 5 The measurements N associated with each point P_i , of depth Z , in the reference set constitute a reference observation X_i .

10 In the same way, the N measurements associated with each point Q_i , of depth Z , in the application set constitute an application observation x .

A first step in the present invention consists in defining in multidimensional space, for example with N dimensions where N is equal to the number 4 of selected
15 logs in the example of the invention, a learning set which comprises all the points P_i and with which each application observation x is compared.

- 20 The form of the learning set, several sections of which are represented in Figures 6A to 9A in the form of cross plots with two dimensions RHOB and DT, or ILD and DT, is defined by characterizing neighbourhood domains D_i . Each neighbourhood domain is centred on a reference
25 observation X_i and is constructed by looking for the k nearest neighbours of each observation X_i . The set of domains D_i constitutes the learning set which, in turn, constitutes a class referred to as the acceptance class C_a . The process for searching for the k nearest
30 neighbours is, in particular, described in the article by DASARATHY B.V. 1991, "NEAREST NEIGHBOR (N.N.) NORMS: nn pattern classification technics" IEEE Computer Society Press TUTORIAL, or O'CALAGHAN J.F. 1975, "An alternative definition for neighborhood of a point",
35 IEEE transactions on computers NOV, 1121-1125.

In a second step, a membership degree to the acceptance class C_a is defined. A decision rule makes it possible to discriminate the observations of an application well

according to its membership degree to the acceptance class C_a . When the membership degree is greater than a first threshold S_1 , the application observation is assigned to the acceptance class C_a .

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When the membership degree of the application observation is less than the threshold S_1 , the said observation is either definitively rejected, in which case it is assigned to a so-called reject class (C_d),
10 or is considered as being ambiguous, in which case it is assigned to a so-called ambiguity class (C_o). This is what is schematically represented in Figure 1, the acceptance C_a , ambiguity C_o and reject C_d classes being schematically formed as ellipses, respectively
15 designated by C_a , C_o and C_d on a cross plot of log 1 and log 2, it being possible for the latter to be RHOB, DT, VSH or ILD.

When the observations of an application well have a
20 high membership degree, it is because they are close to points constituting the learning set and they are generally included in several domains D_i of the said learning set.

25 When the observations of the same application well have a medium membership degree, it can be inferred from this that they are not too far in terms of Euclidian distance from the points in the learning set, but they possibly may not be included in any of the domains D_i .
30 Such observations are then classed in the ambiguity class C_o .

Lastly, when the observations of the application well have a low membership degree, they are considered as
35 being far in terms of Euclidian distance from the points in the learning set, and they are grouped in the reject class C_d .

The membership degree and the assignment to one of the said classes, for the application observations, can be grouped in the form of two logs: a similarity threshold log (or "ST") and a similarity degree log (membership degree log or "MD"), as represented by way of synthetic example in Figure 2, the two logs being represented as a function of depth. On the left-hand part of Figure 2, which represents the similarity degree log, it can be seen that this degree is relatively high for the beds with depths 1000, 1010, 1040 and 1200, and low between depths 1020 and 1030, for depth 1050 and between depths 1060 and 1080. Correspondingly, and for the same depths on the similarity threshold log (right-hand part of Figure 2), it can be seen that an observation made in the application well between depths 1000 and 1015 would be accepted, but between depths 1015 and 1020 it would be considered as ambiguous and therefore assigned to the ambiguity class C_o , and that between depth 1020 and slightly more than depth 1030, it would be rejected and therefore assigned to the reject class C_d . The same comments hold true for the other depths of the application well. For the sake of simplicity and clarity, the three classes of acceptance C_a , ambiguity C_o and reject are represented with different shading, as indicated in the lower rectangles in Figure 2.

In the learning set consisting of the domains which are defined by the known k nearest neighbours process (Figure 3), there are small domains in the strongly populated regions of space, that is to say they have a small sphere radius σ_i , and large domains in the weakly populated regions of space with a high radius σ_i . The small domains lie in the zone of Figure 3 indicated by the arrow F1, and the large domains are indicated by the arrow F2. The radius σ_i corresponds to the Euclidian distance between X_i and its k^{th} nearest neighbour.

The choice to construct overlapping domains with variable size has at least one geological reason. This is because the dispersion of the observations may differ greatly depending on the lithology present in the logging space. For example, observations recognized as characteristic of sandstone formations show much less dispersion than observations associated with clay formations.

Since an excessive size of the domains D_i may pose a problem in terms of the validity of assignment to one of the classes because points which are far apart in terms of Euclidian distance may be assigned to the acceptance class C_a , it is important according to the invention to determine the number k properly, this being so that the isolated points in the learning set are not eliminated. Indeed, isolated points may identify very significant geological facies even if they are not strongly represented and their logging characteristics locate them very much away from the most strongly represented facies.

One important characteristic of the invention therefore relates to the choice of the number k . Since no rule has clearly been defined for determining k in the literature pertaining to the said k nearest neighbours process, the invention advocates construction of the domains on the reference observations so as to characterize the space occupied by these observations. When the number of nearest neighbours k is close to 1, the domains are of small size and essentially do not overlap with one another. The risk of rejecting an observation of an application well while it is projected between several domains is then high. Furthermore, if the number k is increased greatly, this means that there is a great deal of overlap between the domains, then there is a risk of accepting an observation while it is far in terms of Euclidian distance from all the domains. The compromise of the

invention consists in combining the "leave one out" technique with the k nearest neighbours technique. One characteristic of the present invention therefore consists in removing an observation from the learning
5 set and classing this observation on the basis of the $n_a - 1$ remaining observations, and this process is repeated n_a times. The error criterion is the number of application observations not assigned to the acceptance class C_a . The number of nearest neighbours k is chosen
10 so that the error probability is not very high, for example less than 10%.

The degree of membership of each observation x of a well or application set to each of the domains D_i in
15 the learning set is defined by a membership function which can be written in the form of the following expression:

$$\mu_i(x) = e^{\left[\frac{x - X_i}{\sigma_i} \right]} \quad (1)$$

20

in which

X_i is an observation in the learning set, i lying between 1 and n_a ,

n_a corresponds to the number of D_i observations in
25 the learning set,

σ_i is the radius of the domain centred on the observation X_i ,

x is an observation in the application set.

30 The membership of an observation x in the application set to a domain D_i is a maximum for $\mu_i(x) = 1$ and a minimum for $\mu_i(x)$ tending to zero.

The membership degree $\mu(x)$ corresponds to the mean of
35 the k' strongest memberships $\mu_i(x)$ to the domains D_i in the learning set, k' being fixed by the user on the basis of the intended purpose and, in order to limit the effect of isolated points in the classification

process, it is chosen between 1 and k and, preferably, much greater than 1. A choice of k' close to 1 does not make it possible to demonstrate the clay tendency which can be noted in Figures 8C and 8D or Figures 9C and 9D, because of the presence, in the learning sets of Figures 8A and 9A, of a few reference observations corresponding to traces of clay facies, indicated by the three extreme points on the right of Figure 8A or by the three points at the bottom right of Figure 9A.

10

Thus, an observation x lying far from the domains D_i in the learning set has a low degree of membership to the acceptance class C_a and is rejected from said acceptance class C_a if its membership degree is less than a threshold S_1 . However, the said observation x may be considered as ambiguous if its membership degree is greater than a second threshold S_2 .

The decision rule can be written in the following way:

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x assigned to C_a if $\mu(x) \geq S_1$
 x assigned to C_o if $S_2 \leq \mu(x) < S_1$
 x assigned to C_d if $\mu(x) < S_2$

25 An observation x belonging to an application set is projected into a domain D_i centred on an observation in the learning set if the Euclidian distance between x and X_i is less than the radius σ_i of its domain. Consequently, the first threshold S_1 is equal to $e^{-1} \approx$
30 0.3679 by applying the above formula with $x - X_i = \sigma_i$.

The second threshold S_2 must lie between 0 and S_1 . The threshold S_2 makes it possible to define a zone of ambiguity between acceptance and rejection. The large
35 number of tests carried out have allowed the threshold S_2 to be fixed advantageously at a value equal to $e^{-1.3}$. The same tests show that, in the learning set, the error probability connected with the threshold S_2 is about 5%.

Figures 4A to 9D are examples of implementation of the method according to the invention on two application wells A and B.

5

In a field comprising the application wells A and B and reference wells, the intention is to construct a model for estimating the permeability in order to extrapolate it to all the wells in the said field. The learning set
10 which will be established by the logger contains permeability measurements made on core samples taken from four reference wells which have been deemed to be representative of the geological formations encountered on the field. In the examples described, the formations
15 are essentially sandstone/clay with conglomerated facies (deposited in winding channels or meanders and in the flood plain). Prior to this, a stepwise discriminant analysis method has made it possible to evaluate which the most discriminant logs are for
20 estimating the permeability. The logs adopted are given under their commercial abbreviation as defined by the company SCHLUMBERGER, namely RHOB for the density of the formation, DT for the slowness or speed of propagation of the waves in the rock, VSH for the clay
25 index, ILD for the deep resistivity. The N-dimensional space of the method described above therefore corresponds to a four-dimensional space since four representative logs are used.

30 Figure 4A represents the lithology in question at various depths (right-hand part of the figure).

Figure 4B (left-hand part) represents the membership degree under the two log forms, ST for the similarity
35 threshold and MD for the similarity degree. The right-hand part of Figure 4b represents the permeability measured on a core sample, as well as the prediction of the permeability when the four logs RHOB, VSH, DT and ILD are taken into consideration, the prediction being

given with a logarithmic scale ranging from 0.1 to 10,000.

When the similarity degree MD is examined, it is found
5 to be relatively small. This means that there is a low
membership degree to the class C_a , without it being
possible to define the reasons for this rejection,
which is ambiguous in places. This is confirmed by
Figures 6A to 6D, in which Figure 6A represents the
10 learning set and Figures 6B, 6C and 6D respectively
represent the acceptance C_a , ambiguity C_o and reject C_d
classes. In Figure 6B, only a few black points appear,
which signifies that there are very few points similar
with the learning set in Figure 6A, while they are
15 slightly more numerous in the ambiguity class C_o
(Figure 6C) and relatively numerous in the reject class
 C_d (Figure 6D).

To confirm or deny total rejection, the same procedure
20 as before is adopted, each time removing one log RHOB,
VSH, DT or ILD, that is to say the space is reduced to
n-1 dimensions on each occasion.

Figure 7A represents a new learning set which has three
25 dimensions and pertains to the VSH, DT and ILD logs,
the RHOB log having been removed. It is then found that
a large number of points is accepted and assigned to
the class C_a (Figure 7B), and that few points are
considered as ambiguous (Figure 7C) or rejected (Figure
30 7D). The conclusion is that the RHOB log poses a
problem and that this is probably due to a calibration
error for the application well A, or the tool which was
used for determining the RHOB log.

35 Figure 4C represents the ST and MD for each three-
dimensional set, the first representing the result
after elimination of the RHOB log, while the last
represents the result after elimination of the ILD log.
It is found that the observations are all rejected when

they pertain to clay or clay/shale facies. The inference from this is that this facies is not contained in the learning set.

- 5 The following Table (1) summarizes the various comments above.

TABLE 1

STM WELL A	C _a (%)	C _o (%)	C _d (%)
STM with 4 logs	3.89	17.96	78.15
STM without RHOB	78.57	15.97	5.46
STM without VSH	31.93	25.84	42.23
STM without DT	24.89	43.80	31.31
STM without Log ILD	19.22	24.79	55.99

10

The assignment percentages for each class in Table (1) do indeed confirm that the results are much better when the RHOB log is not taken into account, and that this RHOB log has a significant influence in application well A on rejecting the majority of the points.

15

As regards application well B, Figures 5A to 5C and 8A to 9D represent the various results which are collated in Table 2 below.

20

TABLE 2

STM WELL B	C _a (%)	C _o (%)	C _d (%)
STM with 4 logs	54.77	20.83	24.40
STM without RHOB	79.27	16.10	4.63
STM without VSH	79.56	15.24	5.20
STM without DT	75.60	18.03	6.37
STM without Log ILD	83.03	9.16	7.81

- 25 In Figure 5B, analysing the MD and ST logs shows that some of the application observations which are considered as ambiguous correspond, according to the lithology log in Figure 5A, to clay/silt or clay facies

not contained in the learning set. In these facies, the prediction of the permeability is not reliable.

Figure 5C shows that, whether it is the RHOB, VSH, DT or ILD log which is removed, the similarity increases significantly or is of the same order of magnitude.

Referring to the cross plots in Figures 8A to 8D, it can be seen that the majority of the observations for well B are similar to the data in the learning set and therefore assigned to the acceptance class C_a , with an acceptance percentage higher than 75% irrespective of the log removed, with a percentage for the ambiguity class C_o lying between 9 and 18% and a percentage for the reject class C_r lying between 4.63 and 7.81%. However, it should be noted that each time a log is eliminated, accuracy is lost in comparison with Figure 5B which pertains to the membership degree of the four-log set. This is particularly the case when VSH is removed since the increase in the similarity degree MD would imply that the silt and clay facies are included in the learning set, while they are rejected by the other membership degrees. However, this is not the case when comparing the diagrams in figures 8D and 9D, where it can be seen that there is actually rejection of a relatively large number of points, which rejection is confirmed by the MDs of the STM without RHOB, without DT and without ILD on which the clay/silt and clay facies are indeed excluded from the learning set and are consequently not assigned to the acceptance class C_a .

The method according to the invention, which is a similarity threshold method (STM) therefore makes it possible to grade the results of the permeability estimation and identify the silt and clay levels not included in the learning set.

The particular feature of the method according to the invention is that it is independent of the interpretation processes used and that it is very powerful for evaluating the coherence between several
5 sets of data or observations.

Lastly, the method according to the present invention can be applied to numerous cases. It may be used:

- upstream of a logging study, in order to evaluate the
10 coherence of the data between several wells;
- in the scope of an electro-facies characterization or for estimating continuous or discrete measurements;
- for characterizing the representativeness of a zone core-sampled on several wells;
- 15 - in a more geological context, for characterizing from logging viewpoint, of the facies or environments described on the core samples.



1. Method of characterizing the coherence of measurements made in a given medium, of the type consisting in:
 - taking N types of reference measurements at each point (P_i) of a given reference set of the said medium, each point (P_i) being defined by a depth dimension, the group of N measurements which are associated with each point (P_i) constituting a reference observation (X_i),
 - forming at least one N-dimensional learning set containing all the said points (P_i),
 - taking at least N application measurements at each point (Q_i) of an application set of the said medium, which is different from the said reference set, each group of application measurements which are associated with the said point (Q_i) constituting an application observation (x_i),
 - comparing each application observation (x) with all the reference observations (X_i) of the said learning set,characterized in that it furthermore consists in:
 - constructing a neighbourhood domain (D_i) for each reference observation (X_i) of the learning step using the k nearest neighbours process (K-NN), the said neighbourhood domains constituting the said learning set which defines an acceptance class (C_a) for application observations (x) in the application set,
 - defining a degree of membership of the application observations (x) to the said acceptance class (C_a), each application observation (x) being assigned to the acceptance class (C_a) when its membership degree is at least greater than a first threshold (S_1).
2. Method according to Claim 1, characterized in that each application observation (x) is assigned to



one of three classes consisting of the acceptance class (C_a), an ambiguity class (C_o) or a reject class (C_d).

- 5 3. Method according to Claim 1, characterized in that the membership degree comprises at least two thresholds (S_1 , S_2), the second threshold being less than the first threshold (S_1).
- 10 4. Method according to Claim 3, characterized in that an application datum (x) is assigned to the reject class (C_d) when its membership degree is less than the said second threshold (S_2).

- 15 5. Method according to Claims 2 and 3, characterized in that an application datum (x) is assigned to the ambiguity class when its membership degree lies between S_1 and S_2 .

- 20 6. Method according to Claim 1, characterized in that the membership degree is defined by a membership function:

$$\mu_i(x) = e^{\left[\frac{x - X_i}{\sigma_i} \right]} \quad (1)$$

- 25 in which

X_i is an observation in the learning set, i lying between 1 and n_a ,

n_a corresponds to the number of reference observations in the learning set,

- 30 σ_i is the radius of the domain centred on the observation X_i ,

x is an application observation in the application set.

- 35 7. Method according to Claim 6, characterized in that the membership degree $\mu(x)$ corresponds to the mean of the k' strongest memberships $\mu_i(x)$ to the domains D_i in the learning set.



8. Method according to Claim 7, characterized in that the mean k' lies between 1 and k .
- 5 9. Method according to Claim 8, characterized in that the value of k' is very much greater than 1.
- 10 10. Method according to Claim 1, characterized in that, in order to clarify an ambiguity attached to an application observation (x) , an $(n-1)$ -dimensional learning set is constructed, the dimension removed corresponding to one type of measurements.