

METHOD OF ANALYSING FLIGHT DATA

GENERAL TECHNICAL FIELD

The invention relates to a method of analysing a set
5 of flight data recorded during at least one flight of at
least one aircraft.

PRIOR ART

The regulations in terms of maintenance and air
10 traffic define standards that airline companies are
required to comply with in order to ensure to a user a
maximum level of safety.

In order to optimise the maintenance phases, airline
companies have equipped themselves with flight data
15 analysis systems.

Flight data analysis systems known by the name FDM
(Flight Data Monitoring) or instead FOQA (Flight
Operational Quality Assurance) are known. These systems
consist in equipping an aircraft with a flight data
20 recorder. Such a recorder is for example a black box or
instead a specific recorder such as an ACMS (Aircraft
Condition Monitoring System).

These systems enable airline companies to understand
in detail the course of a flight from regular recordings
25 of the values of these flight data made during each
flight of each of their airplanes.

To do this, these systems detect predefined events
occurring during the flight and an expert then analyses
these events, which indicate that a technical incident
30 has occurred during the flight, that a practice or a
condition provided by a flight procedure has not been

complied with, thus giving warning at a very advanced stage of any incidents or accidents that could arise.

These techniques necessitate predefining rules for detecting events, usually defined as exceeding thresholds
5 of one or more parameters, which may trigger alerts so that the expert analyses more closely the flight.

A problem is that these techniques do not make it possible to detect singular events beyond the predefined rules, which may lead to a non detection of an abnormal
10 flight.

DESCRIPTION OF THE INVENTION

Embodiments of the invention seek to make it possible to detect abnormal flights without having the need to
15 define detection rules.

According to an aspect of the present invention, there is provided a method of analysing flight data recorded during N flights of at least one aircraft, by means of a flight data recorder of an aircraft, the data
20 being grouped together by flight i in a signature vector of the flight X_i of size d , the components of which correspond to data recorded during said flight i of the aircraft, a flight i being thus defined by the signature vector X_i , the method comprising the following steps:

- 25 - Gaussian kernel entropy component analysis of the flight signatures X_i to obtain a zone of normal flights and classifying the flight signatures X_i with respect to their distance to said zone;

- determining, for each flight i , an abnormality score z_i defined by the distance of a flight signature X_i with respect to the zone of normal flights;

- detecting, as a function of the abnormality score z_i , at least one abnormal flight,

in which, for each abnormal flight detected, a phantom flight the nearest to the abnormal flight detected is determined while being in the zone of normal flights.

Embodiments of the invention are advantageously completed by the following characteristics, taken singly or in any technically possible combination thereof:

- the parameters of the abnormal flight detected are compared with those of the phantom flight determined in order to detect at least one parameter of the abnormal flight that has rendered abnormal said abnormal flight detected.
- the Gaussian entropy component analysis comprises the following sub-steps:
 - o determination of a matrix of similarity K of size $N \times N$, the components of which quantify the proximity between two flight signatures X_i ;
 - o breakdown into eigen vectors of the matrix of similarity K to obtain N eigen vectors $a_1, \dots, a_N$ and N eigen values $\lambda_1, \dots, \lambda_N$ such that $\forall i=1, \dots, N \quad K \cdot a_i = \lambda_i \cdot a_i$;
 - o determination, for each eigen vector, of its entropy coefficient γ_i

selection of a sub-assembly of eigen vectors $\{a_m\}_{m \in \{1, \dots, N\}}$ such that the sum of the entropies γ_m is greater than the percentage of the sum of the N entropies γ_i .

- the entropy coefficient is defined by

$$\forall i=1,\dots,N \quad \gamma_i = \frac{\lambda_i \cdot \left(\sum_{j=1}^N a_{i,j} \right)}{N^2}.$$

- the abnormality score of a flight i is defined by:

$$5 \quad z_i = 1 - \sum_{k \in m} \frac{(K_i^T a_k)^2}{\lambda_k}.$$

- the components of the matrix of similarity K are defined by:

$$\forall i=1,\dots,N \quad K_{i,j} = \exp \left(- \frac{\|X_i - X_j\|^2}{2\sigma^2} \right),$$

10 where σ^2 is a predetermined bandwidth parameter.

- the bandwidth parameter σ^2 is determined in the following manner:

- o a matrix D of size $N \times N$ is determined
15 corresponding to the distance between two flights and is defined in the following manner

$$\forall i=1,\dots,N \quad D_{i,j} = \|X_i - X_j\|^2;$$

- o each component of each column is arranged in ascending order to obtain a matrix D' ;
- 20 o k first lines of the matrix D' thereby obtained are selected and the others are eliminated to obtain a matrix D' of size $k \times N$;
- o the average of each column of the matrix D' is determined to obtain N values $y_1, \dots, y_N$;

- o the median absolute deviation of the values $y_1, \dots, y_N$ defined by $\text{mad} = \text{mediane}\{y_i - \text{med}\}$ with $\text{med} = \text{mediane}\{y_1, \dots, y_N\}$ is determined;
 - o the bandwidth parameter σ^2 is determined from the median absolute deviation of the values $y_1, \dots, y_N$ by the following functional $\sigma^2 = \max_{y_i < \text{med} + 20 \cdot \text{mad}} \{y_i\}$.
- the data of a flight i are grouped together in a matrix F_i of dimension $T \times P$ with T the number of data recorded during the flight i and P the number of parameters recorded, the vector X_i having for components the columns of the matrix F_i end to end, the vector X_i being then of dimension $d = T \times P$ and is defined by
- $$X_i = [F_i(t=1, p=1), \dots, F_i(t=T, p=1), \dots, F_i(t=1, p=P), \dots, F_i(t=T, p=P)]$$
- .
- the data of a flight i are grouped together in a matrix F_i of dimension $T \times P$ with T the number of data recorded during the flight i and P the number of parameters recorded, the vector X_i having for components the columns of the matrix F_i sampled to select $n < T$ recordings $t_1^i, \dots, t_n^i$ of parameters, the vector X_i being then of dimension $d = n \times P$ and is defined by
- $$X_i = [F_i(t=t_1^i, p=1), \dots, F_i(t=t_n^i, p=1), \dots, F_i(t=t_1^i, p=P), \dots, F_i(t=t_n^i, p=P)]$$

- the data of a flight i are grouped together in a matrix F_i of dimension $T \times P$ with T the number of data recorded during the flight i and P the number of parameters recorded, the vector X_i having for components the average, the variance, the minimal value, the maximal value of a parameter among all the recordings of this parameter, the vector X_i being then defined by:

$$X_i = [\text{mean}(F_i(p=1)), \text{var}(F_i(p=1)), \text{max}(F_i(p=1)), \text{max}(F_i(p=1)), \\ \vdots \\ \text{mean}(F_i(p=P)), \text{var}(F_i(p=P)), \text{max}(F_i(p=P)), \text{max}(F_i(p=P))]$$

10 Embodiments of the invention may have numerous advantages.

 According to embodiments of the invention, the detection of abnormal flights can be automatic and does not necessitate the intervention of an expert for said
15 detection.

 According to embodiments of the invention the detection may be implemented in a statistical manner while taking into account parameters. In this way, there may be an automatic learning that takes place.

20 Embodiments of the invention may enable unexpected problems to be highlighted.

 Embodiments of the invention may enable problems stemming from the contribution of several parameters to be detected.

25 The method according to embodiments of the invention may be used by a non expert in statistics or data mining.

 Moreover, according to embodiments of the invention, the diagnosis of abnormal flights is simple because it makes it possible to create a reference flight, the
30 phantom flight for each abnormal flight detected.

DESCRIPTION OF FIGURES

Other characteristics, aims and advantages of the invention will become clearer from the description that follows, which is purely illustrative and non limiting,
5 and which should be read with reference to the appended drawings, in which:

- figures 1a and 1b schematically illustrate steps of a method according to an embodiment of the invention;
- 10 - figure 2 illustrates a representation of flight data according to an embodiment of the invention.

In all of the figures, similar elements have identical numerical references.

15 DETAILED DESCRIPTION OF THE INVENTION

In a method of analysing flight data in a preliminary step (not detailed) flight data recorded during several flights made by at least one aircraft are recovered.

- 20 These flight data correspond to flight parameters such as for example the speed, the altitude, the temperature, etc.

Then, in a first step E1, it is advisable to extract for each flight i , among all the data recorded during the
25 flight i , those that characterise the flight i in other words the signature of each flight i .

For $N \geq 1$ flights, there are a number P_0 of parameters recorded over a flight time T_0 . By way of example, in certain recorders, it is possible to have up
30 to $P_0 = 2000$ parameters.

It is considered that the parameters are recorded/sampled at the same frequency, if necessary, well known techniques of oversampling and linear approximation are implemented on the data.

5 To extract E1 the data characteristic of a flight i , according to one embodiment, a restriction is made to a flight phase (for example, the landing) of time $T' < T_0$ and only a restricted number $P < P_0$ of pertinent parameters are retained for the analysis of the data of this flight
10 i . By way of example, it is possible to make a restriction to $T'=1000$ seconds and $P=30$ parameters.

Hereafter, the value of each data of the flight i is designated in the following manner: $F_i(t=5, p=1)$ in other words the value of the first parameter recorded at the
15 5th second (if the data are sampled in seconds) for the flight i .

Then, after the extraction E1, in a signature vector X_i of a flight i of dimension d , the data is grouped together E2.

20 Each signature vector X_i thus contains the set of pertinent information relative to the flight i .

The grouping together E2 may be implemented according to three embodiments.

According to a first embodiment, the grouping
25 together E2 in the vector consists in keeping all of the data. This is then known as an exhaustive approach.

According to this first embodiment, to obtain a vector X_i it is advisable to take the matrix F_i and to stick columns one to one.

The vector X_i is then of dimension $d=T \times P$ and is defined by:

$$X_i = [F_i(t=1, p=1), \dots, F_i(t=T, p=1), \dots, F_i(t=1, p=P), \dots, F_i(t=T, p=P)].$$

For example if $T=1000$ and $P=30$ then there is a
5 vector X_i of size 30000 (and not a matrix of size 1000 x 30).

The grouping together according to this first embodiment is useful when one has little extensive job knowledge, and makes it possible to spot quite easily any
10 flight path deviation.

According to a second embodiment, the grouping together E2 in the vector X_i consists in focusing on the value of the parameters at precise instants, which are known as snapshots. These precise instants have an
15 operational sense, for example for the landing phase a snapshot may be made every 1000 feet from 10000 feet of altitude, or then snapshots may be made at instants where particular events take place: landing gear down, etc.

In assuming that n instants of snapshots have been
20 defined then for a flight i the instants of snapshots $t_1^i, \dots, t_n^i$ are noted. It should be noted these instants do not necessarily take place at the same moment for each flight.

The vector X_i is then of dimension $d=n \times P$ and is
25 defined by

$$X_i = [F_i(t=t_1^i, p=1), \dots, F_i(t=t_n^i, p=1), \dots, F_i(t=t_1^i, p=P), \dots, F_i(t=t_n^i, p=P)].$$

This second embodiment makes it possible to obtain better results than with the first embodiment. Indeed, in this second embodiment, since $T \gg n$ there is much less
30 data to process than in the first embodiment.

According to a third embodiment, the grouping together E2 in the vector X_i consists in "summarising" each "curve" of each parameter in a small set of $k \approx 5$ or 10 values: these k values may for example be the average, the variance, the max. value, the min. value of each parameter recorded.

These k values are then combined for all of the parameters to obtain the signature vector X_i of dimension $d = k \times P$ for $k \approx 4$ is defined by

$$X_i = [\text{mean}(F_i(p=1)), \text{var}(F_i(p=1)), \text{max}(F_i(p=1)), \text{min}(F_i(p=1)), \\ \vdots \\ \text{mean}(F_i(p=P)), \text{var}(F_i(p=P)), \text{max}(F_i(p=P)), \text{min}(F_i(p=P))]$$

If for example there are $P=30$ parameters, one then has a signature vector X_i of size $d=120$.

At the end of the grouping together step E2, there are available $N \geq 1$ signature vectors X_i of size d , the components of which correspond to pertinent data recorded during said flight i of the aircraft.

In a complementary manner, each of the components of each signature vector X_i may be normalised E3.

Such a normalisation proves useful when the components of each signature vector X_i have varied orders of magnitude.

In a preferred manner, the normalisation E3 leads to having components of zero average and standard deviation 1 on the set of all of the flights.

X_i is hereafter employed to designate the signature vector of a flight i , the components of which are normalised or not.

The signature vectors X_i are going to undergo several treatments to make it possible to identify if a flight is abnormal.

To do this, a Gaussian kernel entropy component analysis E4 of the signature vectors X_i is going to be implemented to obtain a zone of normal flights E and classifying the signature vectors X_i with respect to their distance to said zone.

In other words, it involves, from all of the flight signatures X_i grouping them together in order to demarcate a zone E of normal flights.

Such an analysis E4 is for example described in the document R. Jenssen: "Kernel entropy component analysis", IEEE transactions on pattern analysis and machine intelligence, vol. 32, n°5, pages 847-860, May 2010.

To carry out the analysis, a matrix of similarity K is determined E41 of size $N \times N$, the components of which quantify the proximity between two signature vectors X_i (in other words between two flights).

This matrix K is known by the name Gram matrix.

The matrix K is obtained from a matrix of the distances D to which a Gaussian function with a predetermined bandwidth parameter σ^2 is applied (the determination of this parameter will be described later).

The matrix K has for expression

$$\forall i=1,\dots,N \quad K_{i,j} = \exp\left(-\frac{\|X_i - X_j\|^2}{2\sigma^2}\right).$$

The bandwidth parameter is obtained by calculation of the distances of each signature vector X_i to its k nearest neighbours with k a whole number between 4 and 10. The value of k depends on the number of flights N and the dimension d .

To determine E42 the bandwidth parameter σ^2 , a matrix D is determined of size $N \times N$ corresponding to the distance between two flights and which is defined in the following manner $\forall i=1, \dots, N \quad D_{i,j} = \|X_i - X_j\|^2$.

Next, for each of the columns of the matrix D , its elements are arranged in ascending order to obtain a matrix D' such that $\forall j=1, \dots, N \quad D'_{1,j} < \dots < D'_{N,j}$.

Next, the k first lines of the matrix D' thereby obtained are selected and the others are eliminated to obtain a matrix D' of size $k \times N$.

Then, the average of each column of the matrix D' is determined to obtain N values $y_1, \dots, y_N$ which represent in fact the average distance of each vector to its k nearest neighbours.

Next, the values $y_1, \dots, y_N$ that are aberrant are eliminated. To do this, one begins by determining med the median value of the set $y_1, \dots, y_N$, which is written $\text{med} = \text{median}\{y_1, \dots, y_N\}$. Next the absolute median deviation of the values $y_1, \dots, y_N$ defined as being the median value of the set $\{|y_1 - \text{med}|, \dots, |y_N - \text{med}|\}$ which is written $\text{mad} = \text{mediane}\{|y_i - \text{med}|\}$ is determined.

Then, the bandwidth parameter σ^2 is determined from the median absolute deviation of the values $y_1, \dots, y_N$ by

the following functional $\sigma^2 = \max_{y_i < \text{med} + 20 \cdot \text{mad}} \{y_i\}$. In other words, all of the values y_i that are greater than $\text{med} + 20 \cdot \text{mad}$ have been eliminated and the largest of the remaining values is chosen as bandwidth parameter.

5 Once the matrix K is obtained, the matrix of similarity K is broken down E43 into eigen vectors to obtain N eigen vectors $a_1, \dots, a_N$ and N eigen values $\lambda_1, \dots, \lambda_N$ such that $\forall i=1, \dots, N \quad K \cdot a_i = \lambda_i \cdot a_i$.

It should be noted that each of the eigen vectors a_i is of size N : $a_i \in \mathbb{R}^N$ and $a_{i,j}$ designates the j^{th} component of the vector a_i . The λ_i are also called the energy coefficients.

From the vectors and eigen values obtained one determines E44 for each eigen vector its entropy coefficient γ_i defined by

$$\forall i=1, \dots, N \quad \gamma_i = \frac{\lambda_i \cdot \left(\sum_{j=1}^N a_{i,j} \right)}{N^2}.$$

The entropy coefficients are a pertinent criterion to select only the most pertinent data in the set of signature vectors of all the flights.

20 In particular, a sub-assembly of eigen vectors $\{a_m\}_{m \in \{1, \dots, N\}}$ is selected E45 such that the sum of the corresponding entropies γ_m is greater than the percentage of the sum of the N entropies γ_i .

In a preferred manner, the percentage is comprised between 75 and 95%, preferably 90%.

The selection of this sub-assembly makes it possible to define a zone of normal flights E going back to the parameters of each vector X_i associated with the selected eigen vectors.

5 In relation with figure 2, if a simple example is considered with two parameters, it is then possible to represent all the flights in a two dimensional graph and it is then possible to determine the zone of normal flights E as being the circle surrounding the cluster of
10 data.

Then, for each flight i , an abnormality score z_i is determined E5, defined by the distance of the flight X_i with respect to the zone of normal flights E.

The abnormality score is defined by $z_i = 1 - \sum_{k \in m} \frac{(K_i^T a_k)^2}{\lambda_k}$
15 with a_k the eigen vectors selected and λ_k their associated eigen values.

The abnormality score is comprised between 0 and 1. The closer the score is to 1, the more the flight is considered abnormal.

20 With reference to figure 2, the flights far from the zone of normal flights E have "abnormal" scores.

In a preferred manner, it is considered that the flights i for which the abnormality score is greater than 0.99 are very probably abnormal and the flights i for
25 which the score is greater than 0.999 are very decidedly abnormal.

Consequently, one detects E6, as a function of the abnormality score z_i , if at least one flight is abnormal.

The abnormality score may be displayed to be viewed by an analyst.

As will have been understood, to determine whether a flight is abnormal, the method uses all the data at its disposal to, itself, determine in what manner a flight may be considered normal and thereby determine which are not. Thus, it is not necessary to put in place detection rules.

If an abnormal flight is detected, for the latter a nominal reference flight known as "phantom flight" the nearest to this abnormal flight detected is determined E_7 while being in the zone of normal flights, the phantom flight being able to be different to a signature flight X_i .

In other words, the phantom flight is defined as the theoretical flight the nearest to the abnormal flight detected while being in the zone of normal flights.

It is in particular the signature Z_0 of the phantom flight that is going to be determined.

The phantom flight has a score z less than 0.99 (or 0.95 if it is really wished to ensure the normality of this flight).

The phantom flight is thus the projection of the abnormal flight detected in the zone of normal flights. In particular, it is the nearest projection.

The phantom flight is generated during the method, it is potentially independent of the flights analysed.

The phantom flight of signature Z_0 associated with an abnormal flight detected of signature X_i is generated via a constrained non linear optimisation procedure. This

optimisation procedure, for a fixed threshold value *seuil*, is expressed in the following manner:

$$Z_0 = \arg \min_{z(Z) < \text{seuil}} \|X_i - Z\|_1.$$

It should be noted that the norm 1 above makes it possible to ensure that the minimum of components are changed between the abnormal flight and its phantom flight.

This optimisation procedure necessitates the calculation of the score $z(Z)$ to obtain the signature Z_0 of the phantom flight.

To do this, the following vector is defined as k_z , valid for all $Z \in \mathcal{R}^d$:

$$k_z = \begin{bmatrix} \exp\left(-\frac{\|Z - X_1\|^2}{2\sigma^2}\right) \\ \vdots \\ \exp\left(-\frac{\|Z - X_N\|^2}{2\sigma^2}\right) \end{bmatrix}.$$

Thus, the function z giving the score of any vector of $\mathcal{R}^d$ is defined by:

$$z(Z) = 1 - \sum_{k=1}^m \frac{(k_z^T a_k)^2}{\lambda_k}.$$

with $a_1, \dots, a_m$ the m eigen vectors retained previously (covering 90% of the total entropy) and $\lambda_1, \dots, \lambda_m$ their associated eigen values.

In relation with figure 2, if the flight corresponding to the parameters referenced 20 is abnormal, the corresponding phantom flight is the flight for which the parameters are referenced 20'.

This makes it possible to compare E8 the parameters of the abnormal flight detected with those of the phantom flight determined in order to detect at least one parameter of the abnormal flight that has rendered
5 abnormal said abnormal flight detected.

CLAIMS

1. Method of analysing flight data recorded during N flights of at least one aircraft, by means of a flight data recorder of an aircraft, the data being grouped together by flight i in a signature vector of the flight X_i of size d , the components of which correspond to data recorded during said flight i of the aircraft, a flight i being thus defined by the signature vector X_i , the method comprising the following steps:

- Gaussian kernel entropy component analysis of the flight signatures X_i to obtain a zone of normal flights and classifying the flight signatures X_i with respect to their distance to said zone;
- determining, for each flight i , an abnormality score z_i defined by the distance of a flight signature X_i with respect to the zone of normal flights;
- detecting, as a function of the abnormality score z_i , at least one abnormal flight

in which, for each abnormal flight detected, a phantom flight the nearest to the abnormal flight detected is determined while being in the zone of normal flights.

2. Analysis method according to claim 1, in which the parameters of the abnormal flight detected are

compared with those of the phantom flight determined in order to detect at least one parameter of the abnormal flight which has rendered abnormal said abnormal flight detected.

3. Analysis method according to claim 1, in which the Gaussian entropy component analysis comprises the following sub-steps:

- determination of a matrix of similarity K of size $N \times N$, the components of which quantify the proximity between two flight signatures X_i ;
- breakdown into eigen vectors of the matrix of similarity K to obtain N eigen vectors $a_1, \dots, a_N$ and N eigen values $\lambda_1, \dots, \lambda_N$ such that $\forall i=1, \dots, N \quad K \cdot a_i = \lambda_i \cdot a_i$;
- determination for each eigen vector of its entropy coefficient γ_i ;
- selection of a sub-assembly of eigen vectors $\{a_m\}_{m \in \{1, \dots, N\}}$ such that the sum of the entropies γ_m is greater than the percentage of the sum of the N entropies γ_i .

4. Analysis method according to claim 3, in which the

entropy coefficient is defined by $\forall i=1, \dots, N \quad \gamma_i = \frac{\lambda_i \cdot \left(\sum_{j=1}^N a_{i,j} \right)}{N^2}$.

5. Analysis method according to one of claims 3 to 4 in which the abnormality score of a flight i is defined by:

$$z_i = 1 - \sum_{k \in m} \frac{(K_i^T a_k)^2}{\lambda_k}.$$

6. Analysis method according to one of claims 3 to 5, in which the components of the matrix of similarity K are defined by:

$$\forall i=1, \dots, N \quad K_{i,j} = \exp\left(-\frac{\|X_i - X_j\|^2}{2\sigma^2}\right),$$

where σ^2 is a predetermined bandwidth parameter.

7. Analysis method according to the preceding claim, in which the bandwidth parameter σ^2 is determined in the following manner:

- a matrix D of size $N \times N$ corresponding to the distance between two flights is determined and is defined in the following

manner $\forall i=1, \dots, N \quad D_{i,j} = \|X_i - X_j\|^2$;

- each component of each column is arranged in ascending order to obtain a matrix D' ;

- k first lines of the matrix D' thereby obtained are selected and the others are eliminated to obtain a matrix D' of size $k \times N$;

- the average of each column of the matrix D' to obtain N values $y_1, \dots, y_N$ is determined;

- the median absolute deviation of the values $y_1, \dots, y_N$ defined by $\text{mad} = \text{mediane}\{|y_i - \text{med}|\}$ with $\text{med} = \text{mediane}\{y_1, \dots, y_N\}$ is determined;

- the bandwidth parameter σ^2 is determined from the median absolute deviation of the values $y_1, \dots, y_N$ by the following functional $\sigma^2 = \max_{y_i < \text{med} + 20 \cdot \text{mad}} \{y_i\}$.

8. Analysis method according to one of the preceding claims, in which the data of a flight i are grouped together in a matrix F_i of dimension $T \times P$ with T the number of data recorded during the flight i and P the number of parameters recorded, the vector X_i having for components the columns of the matrix F_i end to end, the vector X_i being then of dimension $d = T \times P$ and is defined by

$$X_i = [F_i(t=1, p=1), \dots, F_i(t=T, p=1), \dots, F_i(t=1, p=P), \dots, F_i(t=T, p=P)].$$

9. Analysis method according to one of claims 1 to 7, in which the data of a flight i are grouped together in a matrix F_i of dimension $T \times P$ with T the number of data recorded during the flight i and P the number of parameters recorded, the vector X_i having for components the columns of the matrix F_i sampled to select $n < T$ recordings $t'_1, \dots, t'_n$ of parameters, the vector X_i being then of dimension $d = n \times P$ and is defined by

$$X_i = [F_i(t=t'_1, p=1), \dots, F_i(t=t'_n, p=1), \dots, F_i(t=t'_1, p=P), \dots, F_i(t=t'_n, p=P)].$$

10. Analysis method according to one of claims 1 to 7, in which the data of a flight i are grouped together in a matrix F_i of dimension $T \times P$ with T the number of data recorded during the flight i and P the number of

parameters recorded, the vector X_i having for components the average, the variance, the minimal value, the maximal value of a parameter among all the recordings of this parameter, the vector X_i being then defined by:

$$\begin{aligned}
 X_i = & [\text{mean}(F_i(p=1)), \text{var}(F_i(p=1)), \text{max}(F_i(p=1)), \text{max}(F_i(p=1)), \\
 5 \quad & \vdots \\
 & \text{mean}(F_i(p=P)), \text{var}(F_i(p=P)), \text{max}(F_i(p=P)), \text{max}(F_i(p=P))]
 \end{aligned}$$