Multivariate analysis of acoustic emission data as suitable tool to investigate the damage mechanisms in pipelines

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Abstract. The identification of a powerful inspection procedure for buried pipeline is still a relevant problem in industrial field. Several research activities are therefore focused to optimize new online monitoring technologies specifically for pipeline industry. Unfortunately the current available methods can't properly meet the minimum requirement of industrial users. Acoustic emission is a technique that has shown significant potential in this research area. However, many studies give only a qualitative analysis of AE parameters and their distributions, making difficult to propose any automatic non-supervised scheme for the real-time in situ assessment of damage. In this way the information necessary to identify and classify the damage mechanisms that occur during operational conditions could not be sufficient. This paper aims to highlight how the use of multivariable analysis techniques of AE data could be useful in the study of evolution and of the extent of damage in pipelines structures. Unsupervised (k-means method) and Self Organizing Map have been used as analytical instruments.

Introduction

The identification of a powerful inspection procedure for buried pipeline is still a relevant problem in industrial field. Several research activities have been focused to identify new online NDT monitoring technologies specifically for pipeline industry. Unfortunately all current methods can not properly meet the minimum requirement of industrial users.

Acoustic emission (AE) is a technique that has shown significant potentiality in this research area [1-3]. The AE technique is sensitive to the elastic energy spontaneously released when the materials undergo deformation, transformation, or fracture. The AE signals are generated during both activation or propagation of the degradation mechanism. Consequently the AE could be used as a useful tool able to offer a real-time monitoring of damage processes in various kind of structures under load/environmental conditions [4]. Several works in the literature evidences how this technique is widely used for leak detection in pipelines industry [5-6] or to obtain information about the flow of particulate solids within the pipelines [7]. But what it is more interesting is that AE technique can give the opportunity to identify both internal and external cracks/defects on a structure [8], e.g. cracks induced by HIC [9] or by corrosion fatigue [10]. In a pipeline the AE can be generated by several types of fault conditions such as localized fluid-mechanical disturbances, local impingement, erosion, growing fatigue cracks or crack face rubbing, external impacts and leaks. Each damage phenomenon has its specific acoustic wave form identifiable by specific characteristics. Nevertheless, many studies give only a qualitative analysis of AE parameters and their distributions, making difficult to propose any automatic non-supervised scheme for the real-time in situ assessment of damage. In this way the information to identify and classify the damage mechanisms that occur during operational conditions could not be sufficient.

This paper aims to highlight how the use of multi-variable analysis techniques of AE data can be useful in the study of evolution and the extent of damage in pipelines structures. Unsupervised (k-means method) and Self Organizing Map have been used as analytical instruments.
In particular the dimension reduction of large data sets was obtained by means of the Principal Component Analysis (PCA) which is a classical method of multivariate statistics [11]. Kohonen's Self-Organizing Map (SOM) procedure also have been successfully adopted to separate numerically different classes of data [12].
This methodology has in fact proved particularly powerful in identifying, using exemplified topological maps, the evolution and extent of damage of a monitored structure. In this way it is possible to relate each acoustic stage, with unambiguous significant variables, to a specific degradation phase.

Clustering procedures for AE signals
When large datasets of AE signals are collected signals are commonly reduced to a numbers of patterns describing the signal themselves. With the purpose to better identify the AE events a pattern classification in three main groups can be adopted:

- *Common variables*: amplitude, counts, duration, rise-time and energy patterns that are calculated by the acquisition system from the input raw AE wave.
- *Uncommon variables*: they are statistical patterns calculated on the AE hits population such as historic index, severity, RA value and average frequency.
- *Set-up variables*: this group included variables such as time, sensor identification and external variables such as loading condition and so on.

A multi-step procedure able to identify homogeneous clusters of AE signals to be related to specific damage conditions (e.g. tensile crack, or shear cracks, micro cracking or macro-cracking) on the basis of the adoption of the variables dataset can than be adopted. A hardware filtering of the data should be performed at the level of data recording in order to cut off low amplitude noise by means of a high pass filter. Afterwards to analyze the acquired data the suggested procedure include the following steps:

- Clustering noise removal
- Univariate statistical analysis
- Principal Component Analysis (PCA)
- Self Organising Map (SOM)
- Damage Analysis

A scheme of clustering methodology is reported in Figure 1.

Noise removal
At first, when a large database is acquired for long time, it could be useful to apply a seasonality denoising procedure. In this way it is possible discriminate if during specific time intervals (hour, days, seasons..) anomalous events that perturbs population data are recorded. In Figure 2 the contour plot of two AE variables (rise-time and events frequency) as function of day and hours are represented. These graphs are usually used to represent equipotential curves. The different colour regions indicate variables magnitude (right side colour scale).

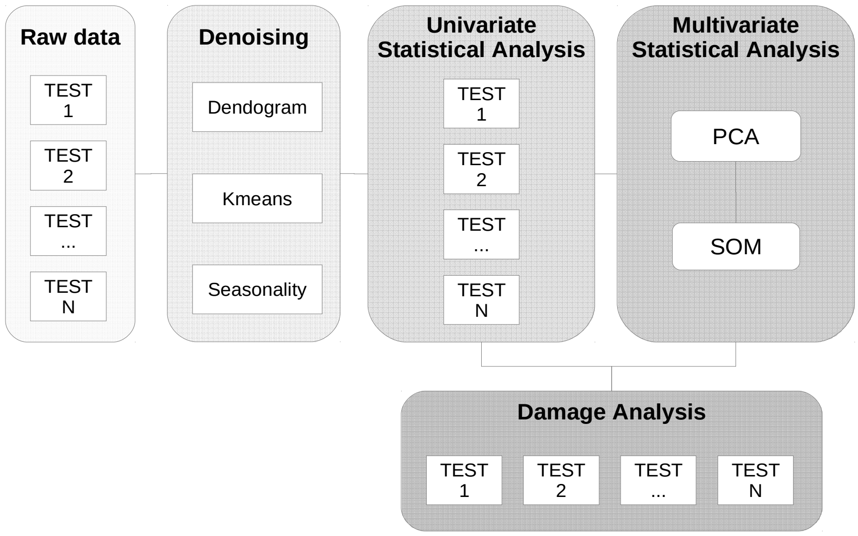

Figure 1. Scheme of the procedure for noise removal and data clustering

Periodic yellow-red colored area on this maps indicate the presence of potential spurious acoustic events. In the reported example [13] the distribution of AE rise-time shows that high values are periodically present in two different specific time span in the range of seven and nineteen o'clock. It can be therefore argued that these events could be probably related with artificial events related to the surrounding environment (external noise). The first step of noise filtering process have therefore to consider the removal of all events present in this time sequence.

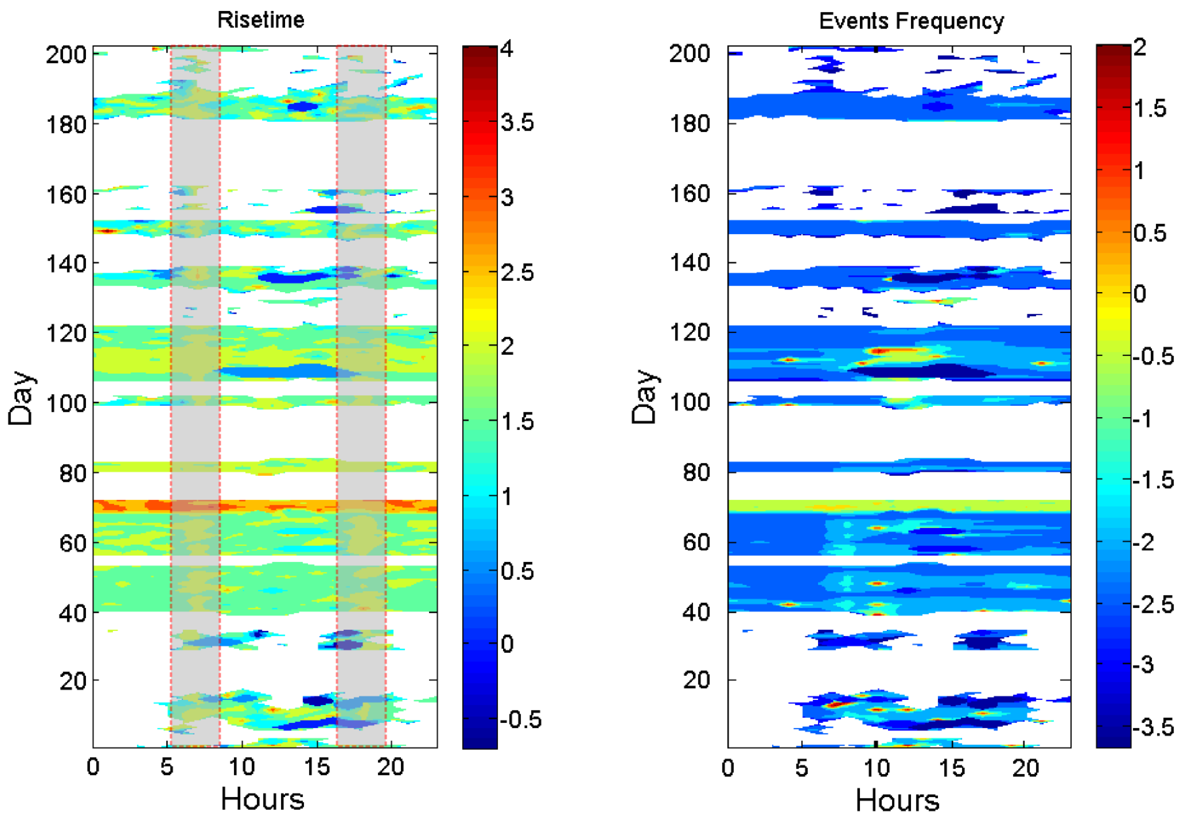

Figure 2. Seasonality denoising procedure: variables classification on the data matrix [13]

Afterwards a further noise removal step can be performed to remove “noisy” cluster. That is, for example, try to remove AE signals when a high number of spurious events were recorded only on daylight time, e.g. cluster including an extremely high number of daylight events (97-98%). Then a PCA analysis and clustering validation can be iteratively performed until no more clusters including a high number of daylight events can be observed. The so filtered data can be finally used as input for univariate and multivariate statistical analysis.

Univariate Statistical Analysis

With the purpose to evaluate the evolution of the acoustic activity during time a plot that relate the cumulative counts versus acquisition time could be used as reported in Figure 3 (the figure is related to AE events collected on a stainless steel bar during SCC test in a magnesium chloride solution [14]). In this case by analyzing the shape of the curve four significant stages, related to specific phases in the damage evolution in the steel sample, can be identified.

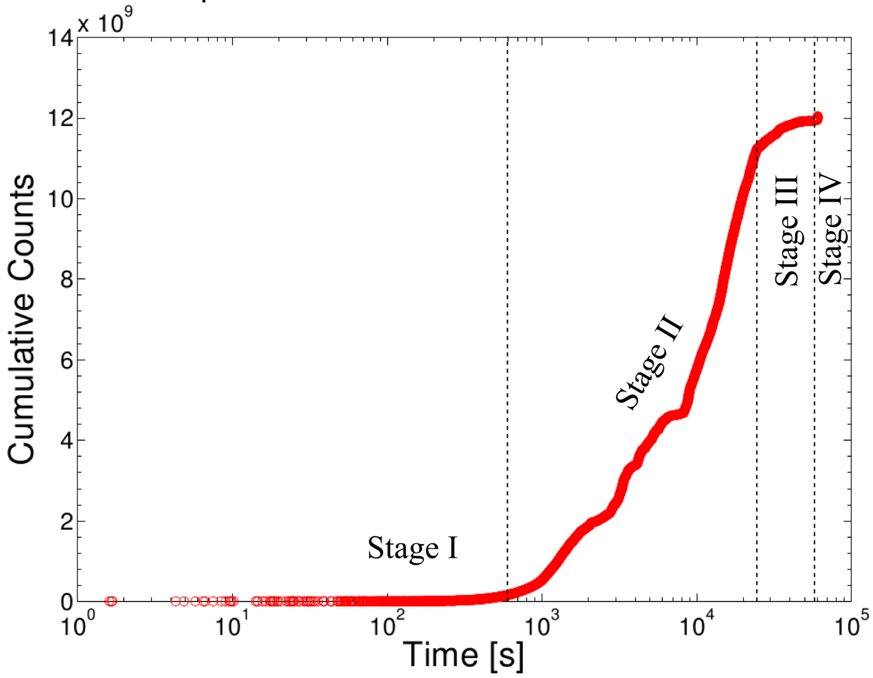

Figure 3. Cumulative counts plot versus time [14]

Stage I: In the early stages of the SCC test (until about 10 minutes) a limited acoustic activity of low intensity has been detected. Acquired acoustic signals were due to the initial electrochemical interaction between the steel sample and the electrolyte solution.

Stage II: After the incubation period, some local corrosion mechanism, e.g. pits, could occur on the metal surface. The pit phenomenon is still not energetically detectable but can induce more relevant SCC mechanism [15]. The crack initiation is followed by short crack propagation, identified with AE at higher amplitude. This behavior is confirmed by the progressive increase of the cumulative counts, related with the activation and propagation of large amount of cracks.

Stage III: After long time there is a quiescent phase where acoustic events become sporadic and energetically with low intensity. In the quiescent phase the time period between two AE events increases significantly. This phenomenon could be related with the formation of a plastic zone at the ahead of the crack during the crack propagation [16]. Increasing the crack size, an intensification of the stress level was

observed, which induces a larger plastic zone ahead of the crack tips. This results in a greater blunting of the crack tip. Larger plastic zone implies that a longer time is needed for crack to resharpen by dissolution for a new further crack propagation. The period of time between two AE events corresponds to the period of material dissolution that induced the crack growth. This could explain the larger time gaps between two AE events during later stages of crack growth.
Stage IV: In this phase the SCC induces progressively a mechanical instability on the wire, until the final fracture of the sample was observed.

Multivariate Statistical Analysis
The Kohonen's self-organizing map (SOM) algorithm [12] can be then useful applied. The SOM analysis related to the SCC damage mechanisms previously described was summarized in the the U-matrix map reported in Figure 4 [14].

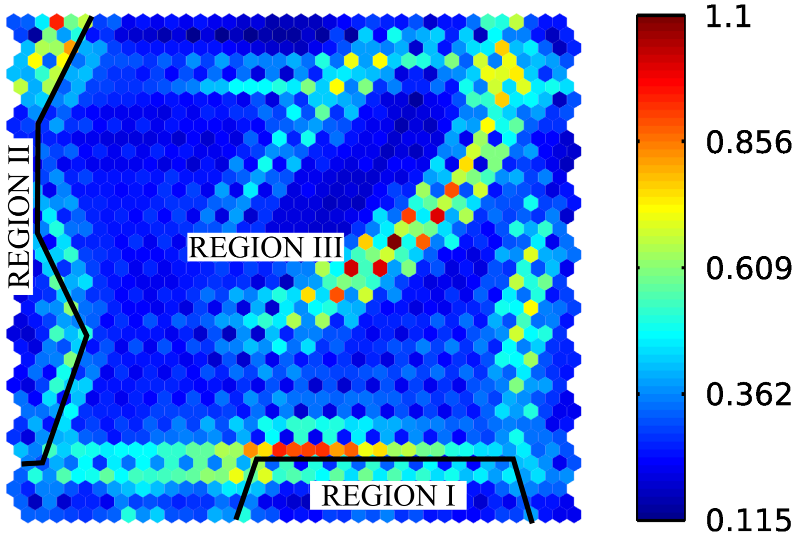

Figure 4. U-matrix resulting from the application of the Kohonen self-organizing map algorithm [14]

This map shows distances from maps units (a unity of data cluster related to “similar” events) and their nearest neighborhood, evaluated by Euclidean method. High values of U-matrix map (red and yellow pixels) identify large distances between neighboring map units. Therefore uniform areas of low value (blue pixels) group together elements belonging to the same cluster. In this specific case, we identified many relevant discriminated areas related with a specific cluster. It is interesting to note that using the topological maps of the variables (reported in Figure 5) it should be possible, on the basis of variable magnitude distribution, to relate data cluster to local area of specific variables. In particular, we defined three regions on the U-matrix map. The definition of the area associated to the first region is heavy influenced by the event frequency distribution as can be observed in the topological map (Figure 5).
In fact the events characterized by high event frequency (red and yellow pixels in the event frequency topological map) are grouped in the bottom-right corner of the map. A second region can be identified in a large area located in the middle of the U-matrix map. Here some sub-cluster are identifiable. In particular AE with high rise-time and low average frequency are grouped on the bottom-left of the map. At the same time a second cluster identified by low RA and medium event frequency is located on the right of the map. Furthermore on the top-left of the map a third cluster is related to

low energetic acoustic events. A large region, located on the center of the map, is heavily influenced by rise-time. Finally on top right corner are grouped all events with high amplitude. A third region, related with the quiescence phase, is located on the left of the U-matrix map.

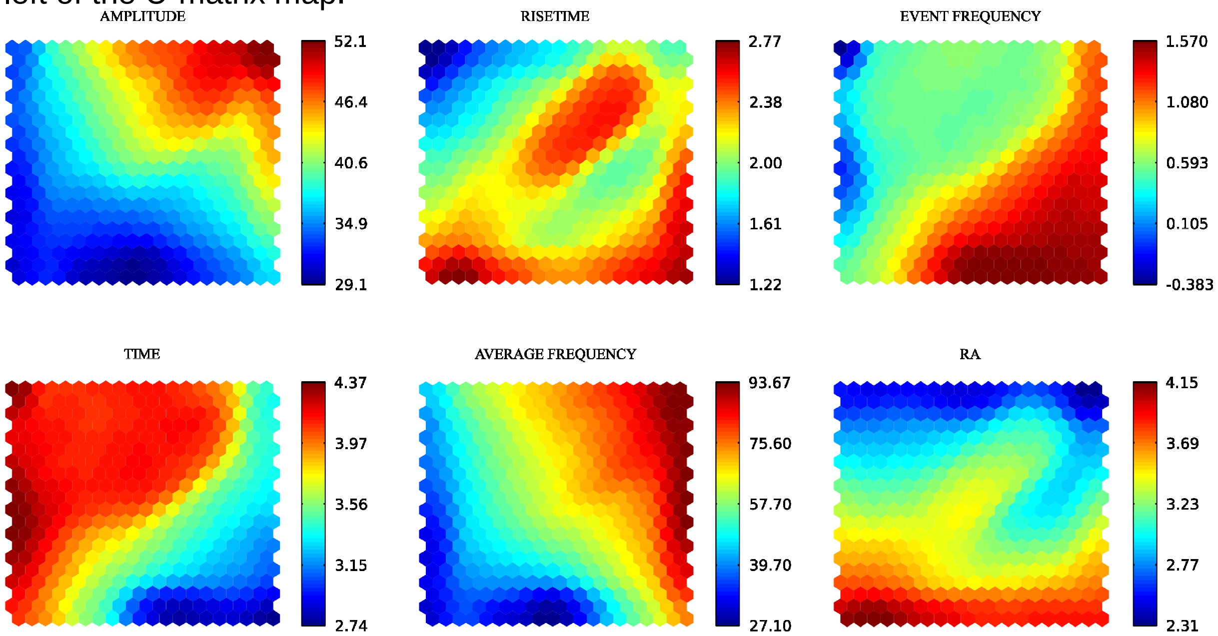

Figure 5. Topological maps of the uncorrelated variables as resulted from the application of Kohonen's self organizing map algorithm [14].

Damage analysis

The ratio between rise-time and amplitude (defined as RA value) can be considered as a relevant parameter to define a specific acoustic emission. Each crack propagation mode can be related with a specific waveform. In this way, on damage analysis procedure, the RA value could be used as a discriminant parameter to identify tensile and shear crack propagation [17-18]. Low RA value are usually related with a tensile crack propagation [19]. In fact, when the crack propagates in accordance with the mode I (tensile mode), the walls of the crack are moving away one each another, resulting in a transient change in volume of the material. In this case most of the energy generated is transmitted in the form of a longitudinal wave. There will be a small amount of shear waveform, which will propagate with a lower speed. Consequently, the large part of the energy is released in the first phase of the wave generation (Figure 6 top images), where the waveform is characterized by a small value of rise-time and high amplitude.

Instead, when the crack propagates according to the mode II (shear mode) it has a relative sliding between the walls of the crack, consequently there is only a shape variation of the material (the volume remains unmodified). In this case the shear wave energy contribution becomes significant compared to the longitudinal contribution longitudinal determining a high rise-time and therefore high value of the parameter RA (Figure 5 lower images) [20].

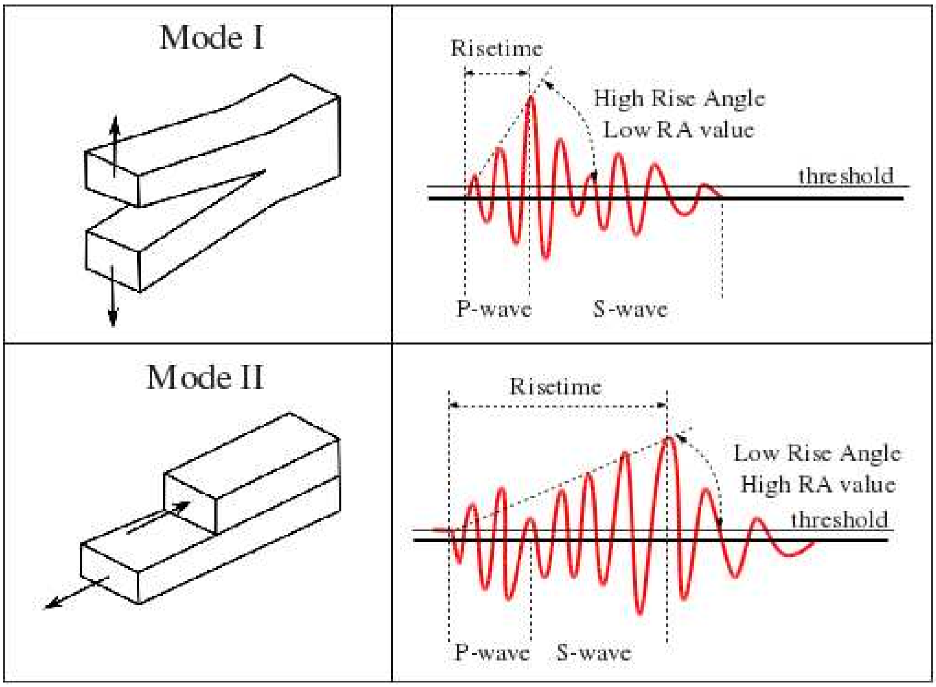

Figure 6. Relation between crack propagation mode and AE waveform RA parameter [20].

At this point it could be intriguing to relate the damage evolution of the sample due to the corrosive conditions imposed by the test set-up to the above mentioned outcomes. On the basis of the above reported considerations it may be possible to divide the U-matrix map into specific damage mechanism areas, according to the schematic representation shown in Figure 7, in which we can distinguish the activation, propagation and quiescence, respectively related to areas I, II and III. A specific section was underlined to identify the failure damage area. Where possible, the section II was divided in sub-cluster with the purpose to evidence the evolution of the crack propagation mode during the SCC test.

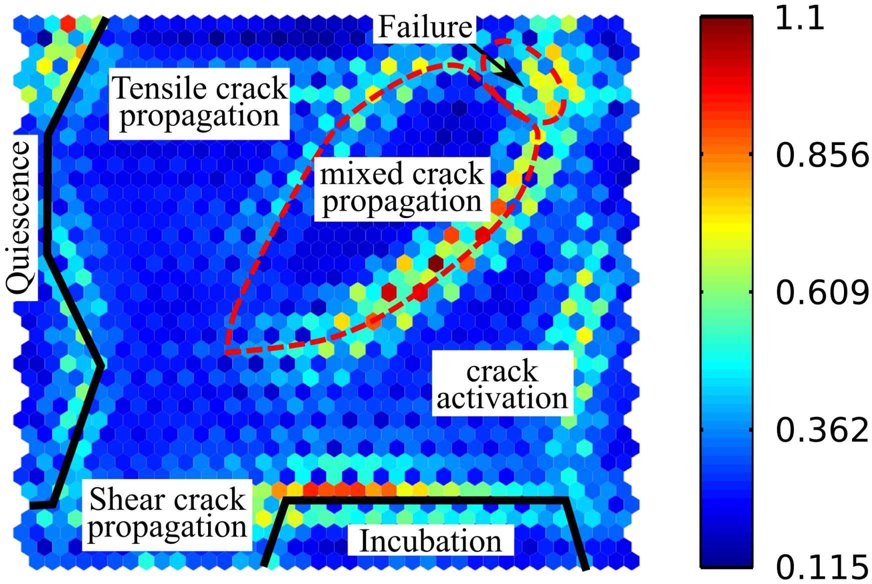

Figure 7. Damage detection mechanism areas as identified by SOM [14]

Such procedure can be applied also to multiple configuration and try to identify the specific differences related to different damage mechanisms. The Figure 8 [21] evidences the applicability of SOM analysis to large dataset constituted by a different test conditions. By this way, this procedure could be used to evaluate simultaneously AE database of different failure events recorded during in-situ monitoring, giving a support in the identification of stability or potential instability of a structure.

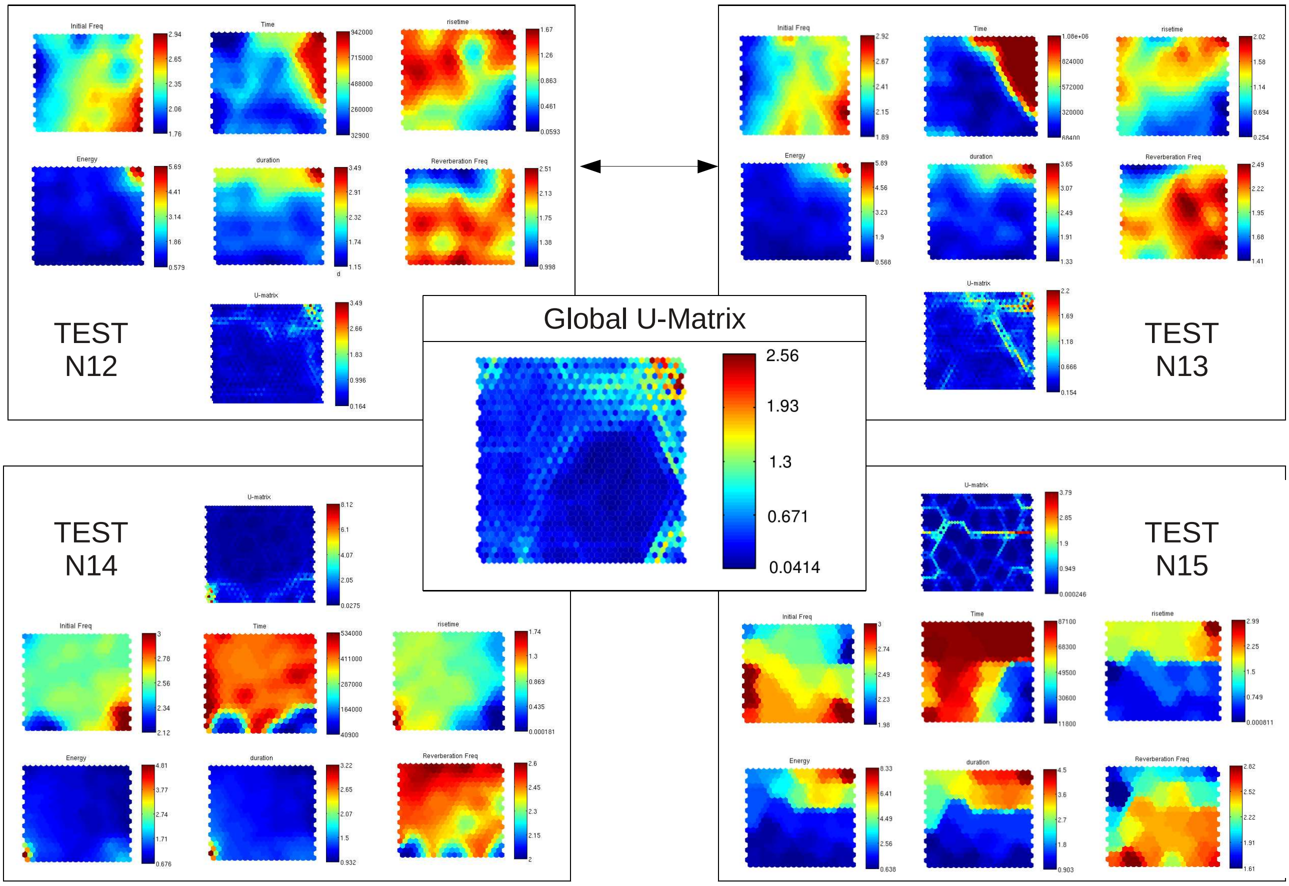

Figure 8. Partial and global SOM with topological maps of the variables for four different SCC test conditions applied on stainless steel bars [21]

Conclusions

The use of multivariable analysis techniques of AE data was suggested as a useful tool to evaluated corrosion mechanism and damage extension in buried pipelines.

Some example of the application of cluster analysis procedures to identify cracking mechanisms in steel components have been reported. Two different clustering procedures based on the adoption k-means algorithm as well as Principal Component Analysis and Self Organizing Map algorithms have been proposed. A procedure based on cluster analysis was developed to remove AE noise signal. Results obtained are highly promising for industrial applications (chemical, petrochemical, civil, etc…) were large database are usually necessary to verify or forecast the stability/ integrity of a structure. Further improvements of the algorithms and the development of a validation procedure are however still necessary for practical application.

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