INGV-DPC V4 PROJECT

PROJECT V4: "CONCEPTION, VERIFICATION, AND APPLICATION OF INNOVATIVE TECHNIQUES TO STUDY ACTIVE VOLCANOES"

BY

THE ISTITUTO NAZIONALE DI GEOFISICA E VULCANOLOGIA (INGV)

AND

THE ITALIAN DEPARTMENT FOR CIVIL DEFENSE (DPC)

U.R. V4/10 - *WP3.1: REAL-TIME ESTIMATION OF EARTHQUAKE SOURCE PARAMETERS*.

REPORT

AUTOMATIC ANALYSIS OF SEISMIC DATA BY USING NEURAL NETWORKS: APPLICATIONS TO ITALIAN VOLCANOES.

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Abstract

The availability of the new computing techniques allows to perform advanced analysis in near real time, improving the seismological monitoring systems, which can extract more significant information from the raw data in a really short time. However, the correct identification of the events remains a critical aspect for the reliability of near real time automatic analysis. We approach this problem by using Neural Networks (NN) for discriminating among the seismic signals recorded in the Neapolitan volcanic area (Vesuvius, Phlegraean Fields). The proposed neural techniques have been also applied to other sets of seismic data recorded in Stromboli volcano. The obtained results are very encouraging, giving 100% of correct classification for some transient signals recorded at Vesuvius and allowing the clustering of the large dataset of VLP events recorded at Stromboli volcano.

1. Introduction

Active volcanoes produce a wide variety of seismic events related to different physical processes. A systematic and efficient monitoring of the volcanic activity helps in eruption forecasting and provides the scientific data to understand the structure and dynamics of the volcanoes.

A key contribute to the monitoring improvement is the automation of many functions, which can enhance the capability to analyze several types of data in short time and to determine the significant parameters for volcano status description. Thus, an effective automatic strategy for the detection and discrimination of seismic signals integrated into an analysis system in real time could considerably reduce the heavy and time-consuming work of the experts without affect the monitoring system reliability.

Several methods exist in literature for the detection and discrimination of different typologies of seismic signals (Hartse et al., 1995; Gitterman et al., 1999; Joswig 1990; Rowe et al., 2004). However, encouraging results have been reached also with the neural networks (Dowla et al., 1990; Cercone and Martin, 1994; Dowla, 1995; Tiira, 1999; Del Pezzo et al., 2003; Scarpetta et al., 2005).

Our application mainly regards the Neapolitan volcanic area (Vesuvius, Phlegraean Fields). The aim is to apply the neural automatic system for discriminating the Volcano-Tectonic (VT) events from false signals, i.e. those generated by external sources (quarry o undersea artificial explosions) or natural events (thunders).

Moreover also the seismicity of the Stromboli volcano is taken into account. In this case, the neural system is able to classify other typologies of seismic signals, i.e. the explosion-quakes, the landslides, the volcanic microtremor and the Very Long Period (VLP) signals associated with the explosions.

A crucial aspect for a correct classification of the seismic signals by using a neural strategy is the data preprocessing or feature extraction step. Thus, it is important to describe appropriately the seismic signal through some characteristics or *features* which represent it in a compact and significant way allowing its analysis and the comparison with other data. In particular, we have considered the *Linear Predictive Coding* (LPC) (Makhoul, 1975) and a *Waveform Parameterization* which characterize adequately the seismic signal in the frequency and time domain respectively.

Finally, the obtained codified signal is discriminated opportunely using neural algorithms. In particular, for the classification task is applied a supervised neural network, the Multi-Layer Perceptron (MLP) (Bishop, 1995), while an unsupervised analysis of the seismic signals is performed using the Kohonen Self-Organizing Map (SOM) (Kohonen et al., 1996; Kohonen, 1997), in order to validate the neural automatic strategy as well as to cluster huge high-dimensional datasets with no a-priori information.

2. Neural Networks

The Neural Networks (Haykin, 1999) are computational models inspired to human brain behavior. Figure 1 shows a biological neuron and its mathematical abstraction. The first model consists of several dendrites (input connections), which are connected via synapses to other neurons, and one axon (output connection). If the sum of the input signals exceeds a certain threshold value, then the neuron fires and an output signal is transmitted down the axon.

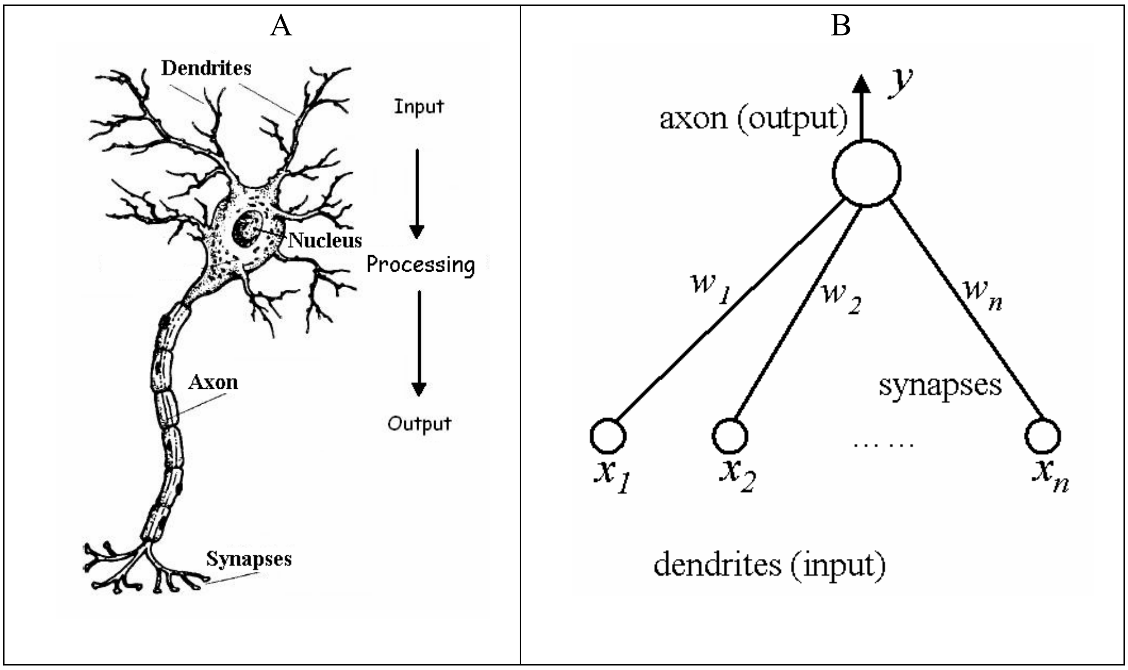

Fig. 1: The biological (A) and the artificial neuron (B).

The artificial neuron is an abstraction of biological neuron and represents the basic unit in an artificial neural network. It receives one or more inputs (representing the one or more dendrites), shown as x_1, x_2, ...x_N in the figure 1, and sum them to produce an output. To each input is associated a weight, denoted as w_1, w_2,.., w_N, which correspond to the synaptic connections in the biological neuron. The weighted sum of each node is passed through a non-linear function known as an activation or transfer function, whose typical form is the sigmoid, but other kinds can be considered.

A neural network acquires the knowledge through a learning process and store it within inter-neuron connection (synaptic weights). Basically, learning is a process by which the network adapts itself to the external stimulus so that it can produce the correct output.

The general structure of a neural network is composed of:

- a set of processing units (input - hidden - output);
- an activation state $a_i(t)$ for each unit u_i at time t and an activation function $f_i(a_i(t))$ determining the network output;
- a connection scheme among the states or network architecture or topology (single or multi-layers);
- a learning algorithm which controls the network adaptation process to the external stimulus. An error function is defined on the net output characterizing the quality of the learning.

The NN implement the *learning by examples*, realized modifying the weights on the connections in order to minimizing the error function. In relation to the learning process, the neural networks can be *supervised* or *unsupervised*.

In a supervised neural network the learning process requires a pre-classified subset of data (i.e., a certain number of input/output examples) to train the net. Thus, the dataset will be divided into a training and testing set, containing different data from the training set, that will allow to test the network generalization capability. The model of supervised network used for our classification task is the Multi-Layer Perceptron (MLP).

In an unsupervised neural net the network output is unknown, meaning that the learning process does not need a previous data classification. The network uses neurobiological principles, such as Hebbian learning and competitive approaches, to discover the similarity in the data structure. These networks allow to process huge datasets with high-dimensional input vectors. Thus, they are extensively used in data mining applications and large datasets clustering. The model of unsupervised network applied for our clustering task is the Self-Organizing Map (SOM).

2.1 Supervised Neural Network: MLP

For the classification of the seismic data we have used a feed-forward MLP (Fig. 2). The network structure is organized in layers: an input layer, one or more hidden layers and an output layer.

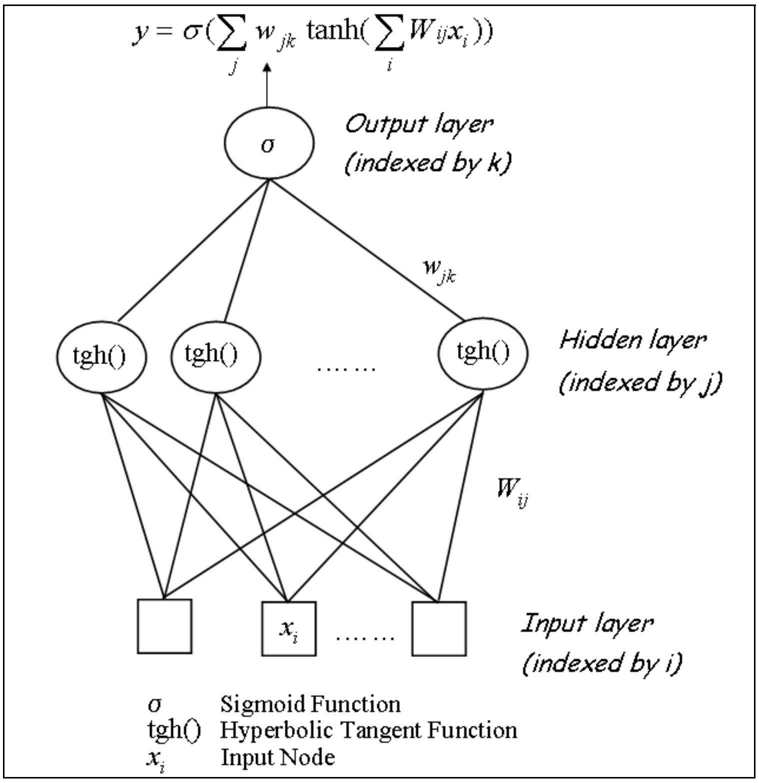

Fig. 2: The structure of a MLP network..

No intra-state connections are present in the network neither feed-back connections (i.e. feed-forward). The activation functions are the sigmoid (σ) for the hidden units and the Hyperbolic tangent (tgh) for the output units. The network output is calculated as:

$$y = \sigma(\sum_j w_{jk} \tanh(\sum_i W_{ij} x_i))$$

where W_{ij} are the weights on the connections from the input to the hidden layer and w_{jk} the weights on the connections from the hidden to the output layer. The network output has a probabilistic interpretation, i.e. it represents the probability of the net input to belong to a specific class of events.

If the discrimination is between two sets of signals the output layer has a single unit while for the three-class discrimination there will be three output units (Esposito et al, 2006 c).

This kind of network is mainly applied when the data are not-linearly separable.

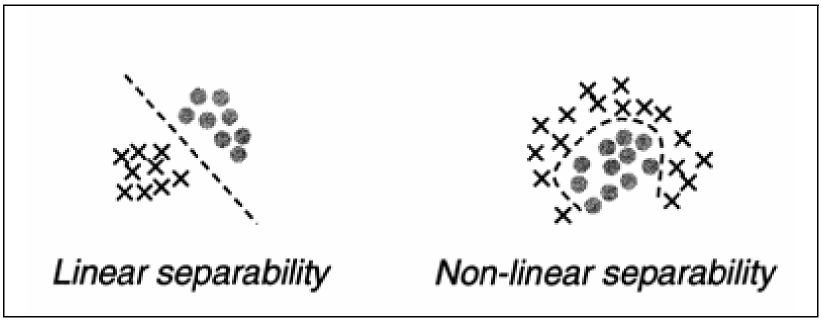

Fig. 3: Linear and non-linear separability of the data.

2.2 Unsupervised Neural Network: SOM

For the unsupervised analysis and clustering of the seismic data we have exploited the Self-Organizing Map (SOM) (Fig. 4).

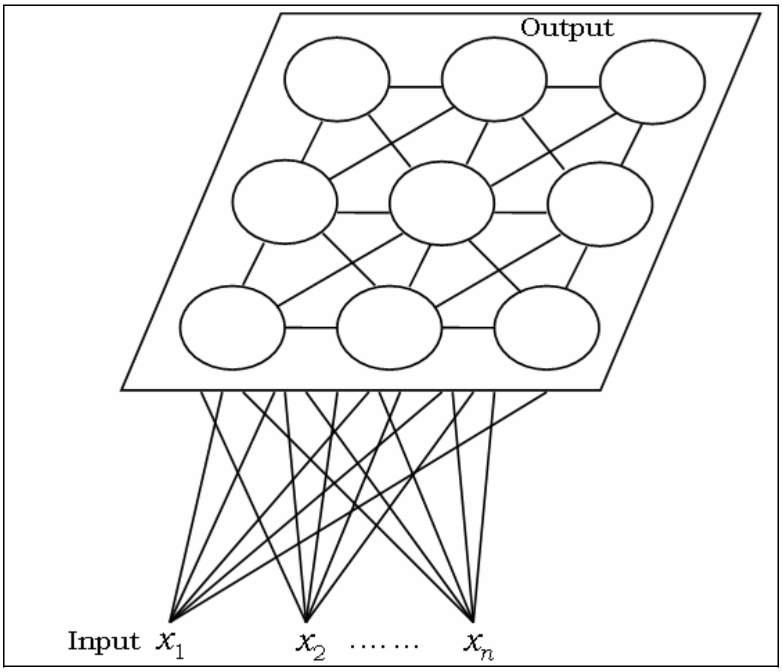

Fig. 4: A schematic architecture of the SOM.

The SOM network presents an input layer and an output layer: each input is connected to all output neurons organized on a bi-dimensional grid. To each node is associated a prototype vector or weight vector and adjacent nodes are connected by a neighborhood function defining the map topology. The basic SOM algorithm (*winner take all*) is iterative and sequential. Formally, at each iteration t:

- an input vector x(t) is randomly extracted;

- the winning node c (Best Matching Unit) is found by comparing the input and prototype vector $\mathbf{m}_i(t)$ of all nodes (competitive aspect) by using the Euclidean distance metrics (||·||). Explicitly, the BMU is identified by the condition:

$$\forall i, \left\|\mathbf{x}(t) - \mathbf{m}_c(t)\right\| \leq \left\|\mathbf{x}(t) - \mathbf{m}_i(t)\right\|$$

- the winning node's prototype and its topological neighbors (cooperative aspect) are then updated according to the rule:

$$\mathbf{m}_i(t+1) = \mathbf{m}_i(t) + h_{c,i}(t)(\mathbf{x}(t) - \mathbf{m}_i(t))$$

  where $h_{c,i}(t)$ is the Gaussian decreasing neighborhood function of distance between the i-th and c-th node on the map grid.

The SOM algorithm carries out a non-linear mapping of input data onto a two-dimensional grid preserving the most important topological and metric data relationships.

The SOM (Kohonen et al., 1996) has proven to be an efficient tool for data exploration tasks in various applications.

3. Feature Extraction Stage

An important phase of the data classification or clustering by using the neural networks is the pre-processing or feature extraction stage. The aim is to perform a transformation from data space into a feature space in order to remove redundancy from data, extract robust information and represent them in a compact form. The critical point is to identify the appropriate features which are significant for the specific application.

Usually, to characterize univocally the seismic signal we codify it in the frequency and time domain through spectral content and waveform features. The joint exploration of these two features is due to the fact that this information is the same used by the analysts in the visual classification of the events.

The procedures employ for extract this information from the signal are the Liner Predictive Coding (LPC), which gives the spectral features, and a Waveform Parameterization, which returns the temporal characteristics.

The LPC is a technique mostly used in audio signal processing and speech analysis for representing the spectral envelope of a speech signal in a compressed form, using the information of a linear predictive model. The basic idea of the LPC algorithm is to model each signal sample s_n at time n as a linear combination of a certain number p of its past values as shown below:

$$s_n^* = \sum_{k=1}^{p} c_k s_{n-k} + G$$

where c_k are the *prediction coefficients*, G is the *gain* and p represents the *model order*. The choice of p is problem dependent. The c_k estimation is obtained by an optimization procedure which minimizes the error between the real value of the signal sample and its LPC estimate. The coefficients c_k efficiently encode the signal frequency features.

For waveform feature extraction we use a function computed as the difference, properly normalized, between the maximum and minimum signal amplitudes within a 1-sec sliding window.

4. Application Areas and Results

The seismic zones under examination are the Neapolitan volcanic area (Phlegraean Fields, Vesuvius) and the Stromboli volcano (Fig. 5) (Giudicepietro et al, 2007).

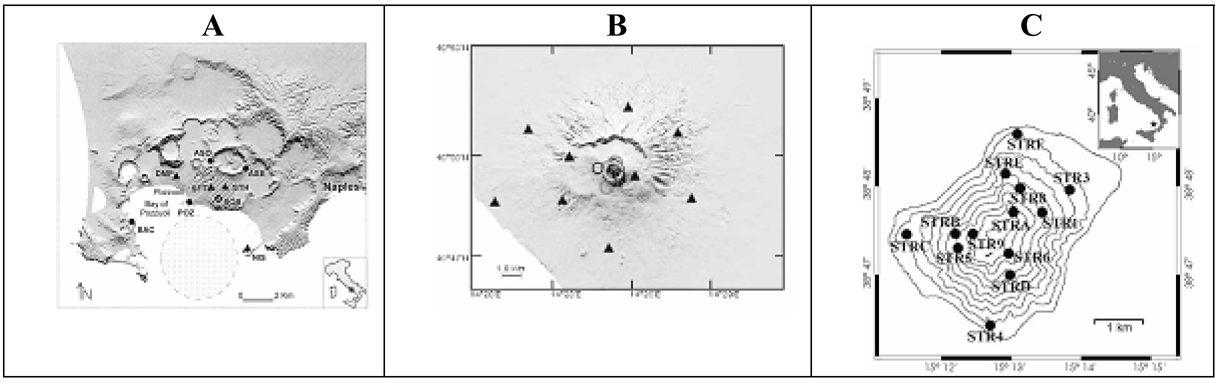

Fig. 5: The seismic areas under examination: the Phlegraean Fields (A), the Vesuvius (B) and the Stromboli volcano (C) .

4.1 Phlegraean Fields

For the Phlegraean Fields (Del Pezzo et al, 2003) the intend is to distinguish between the artificial events, i.e. the undersea explosions generated by fishermen in Pozzuoli bay, and the volcano-tectonic earthquakes. In this case, for the feature extraction stage, we apply the LPC method and so we encoded the seismic signals using only their spectral features. For the classification we use a MLP-based discriminator. On the test set the neural net gave a classification performance of 92%, demonstrating a good generalization capability.

4.2 Vesuvius

For the Vesuvius (Scarpetta et al, 2005) the aim is to discriminate between the local seismic signals, which can cause false event detection, and volcano-tectonic earthquakes. In particular, we want to distinguish between couples of signal types recorded at the same seismic station. The classes of signals (Fig. 6) under examination are:

- earthquakes
- quarry blasts - limestone
- underwater explosions
- quarry blasts - pyroclastics
- thunders

In the preprocessing phase we use the LPC technique and a waveform parameterization representing the signals through their spectral and waveform features. For the classification task, we implement a specialized supervised two-class MPL-based automatic classifier for each couple of signal typologies.

Table 1 reports the MLP network Performance (percentage of correct classification on test sets) for each classification task.

Classification Task	Performance
earthquakes/quarry blasts - limestone (NL9)	100%
earthquakes/underwater explosions (CPV)	99%
earthquakes/thunders (BKE)	98%
earthquakes/quarry blasts - pyroclastic (TRZ)	95%

Table 1: Net classification performance for the Vesuvius dataset.

It is possible to observe that the joint use of spectral and temporal features improves the net performance with respect to the previous work (Del Pezzo et al, 2003). This means that both features provide a significant contribution to the discrimination, and play a critical role in obtaining a reliable system.

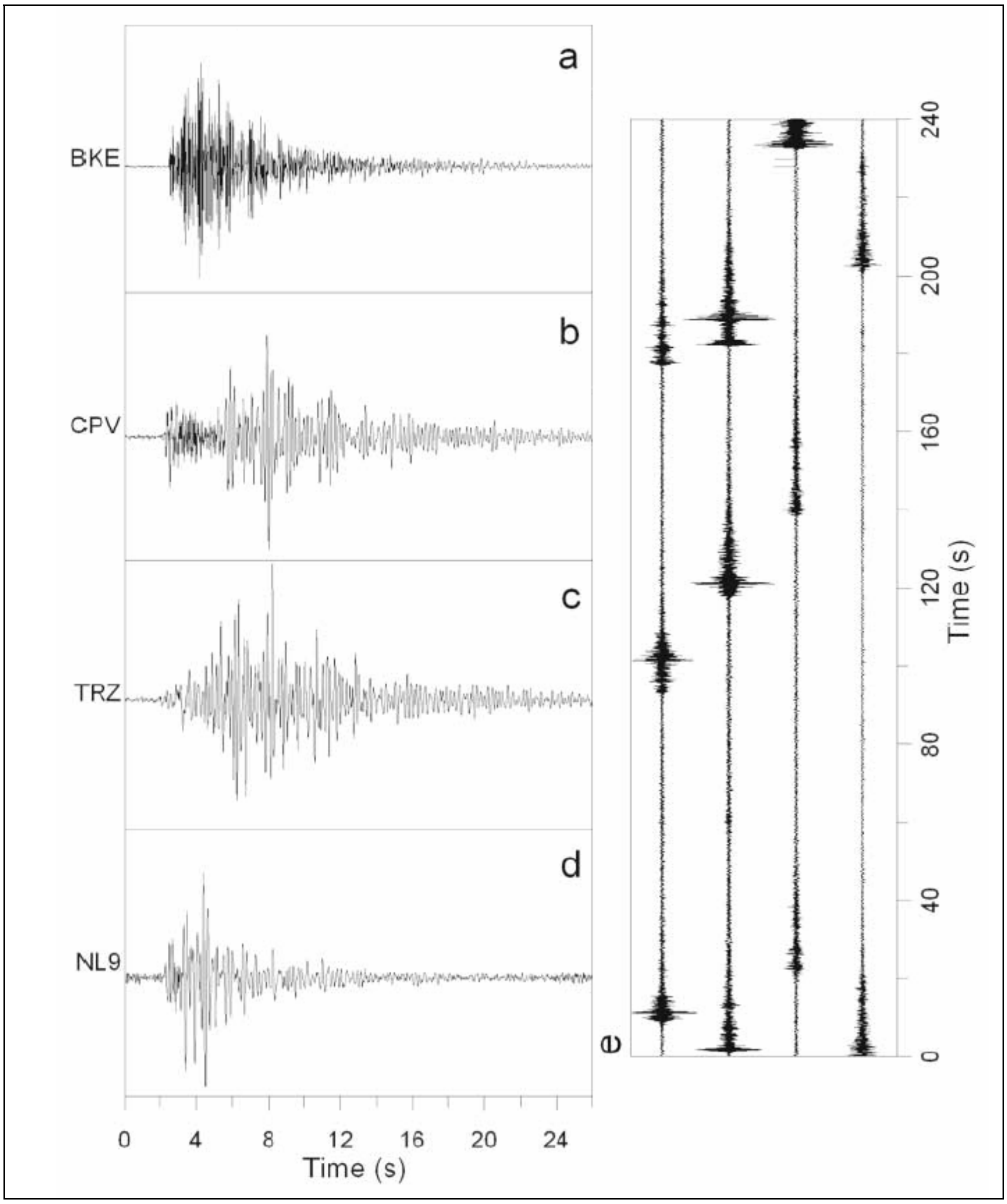

Fig. 6: Typical waveforms of Vesuvius events: a) VT earthquake (at BKE station), b) undersea explosion (CPV), c) quarry blast in pyroclastic caves (TRZ), d) quarry blast in limestone caves (NL9), e) a sequence of thunders (BKE).

On the Vesuvius dataset it has been realized also an unsupervised analysis (Masiello et al, 2005) using the SOM algorithm. In this case the task is more complex because the aim is not the two-class discrimination but the clustering of all the five typologies of events. Still the signals are preprocessed and so encoded by their frequency content, extracted by the LPC technique, and time-domain information, obtained by using the waveform parameterization. The SOM works without assumption about the data distribution and no external information, like previously expert classification, is provided to obtain the final output. Thus, the class labels have been used afterwards to aid in the interpretation of the results, without affecting the structures that have been found.

The results (Fig. 7) show that the SOM gives a good representation of the cluster structure and a good separation of the five classes of signals identified by the experts.

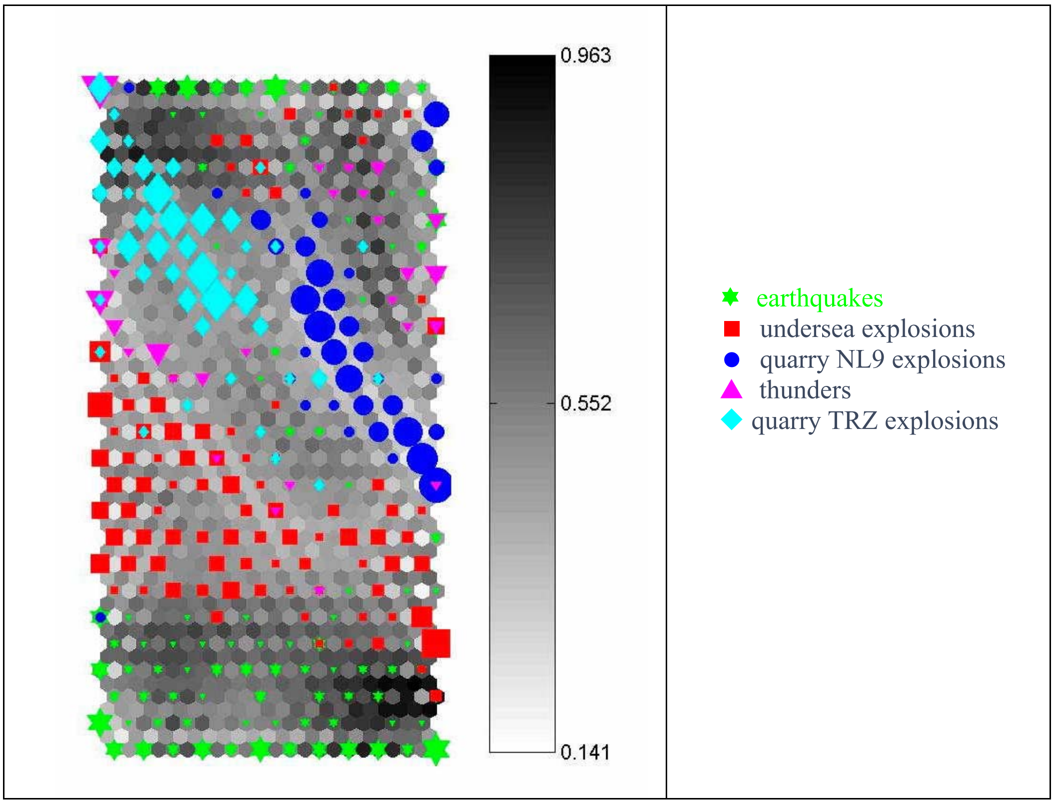

Fig. 7: The SOM map (with 312=26x12 nodes) for the Vesuvius data. The node's size represents the number of signals clustered in that node (data density). The gray hexagons separating the nodes indicates the Euclidean distances between the prototypes. Thus, high distance values correspond to dark gray hexagons.

4.3 Stromboli

For Stromboli (Esposito et al, 2006 c) the aim is to distinguish the seismic signals due to landslides from explosion-quakes produced by the volcano. In order to implement the method on a continuous data stream we also considered to separate these events from the volcanic microtremor that is the background of seismic wave-field of Stromboli volcano. The dataset is composed of:

- explosion-quakes
- landslides
- microtremor signals

Figure 8 shows the typical waveforms and the spectrograms of these signals. From the figure it is possible to note that while the explosion-quake (A) and the microtremor signal (C) exhibit limited frequency content (1-6 Hz), the landslide (B) has a broader spectrum. The explosion-quakes are characterized by a signal exhibiting no distinct seismic phases. Landslide signals are higher in frequency than the explosion-quakes and their typical waveform has an emergent onset. The microtremor is a continuous signal having frequencies between 1 and 3 Hz.

After the feature extraction step, the signals are represented as feature vectors obtained using the LPC and the waveform parameterization. For the classification we implement a MLP-based classifier for the two and three-class discrimination tasks to distinguish between couples of events (explosion-quakes/landslides, landslides/microtremor and explosion-quakes/microtremor) and among landslides, explosion-quakes and microtremor signals. The obtained results are reported in Table 2.

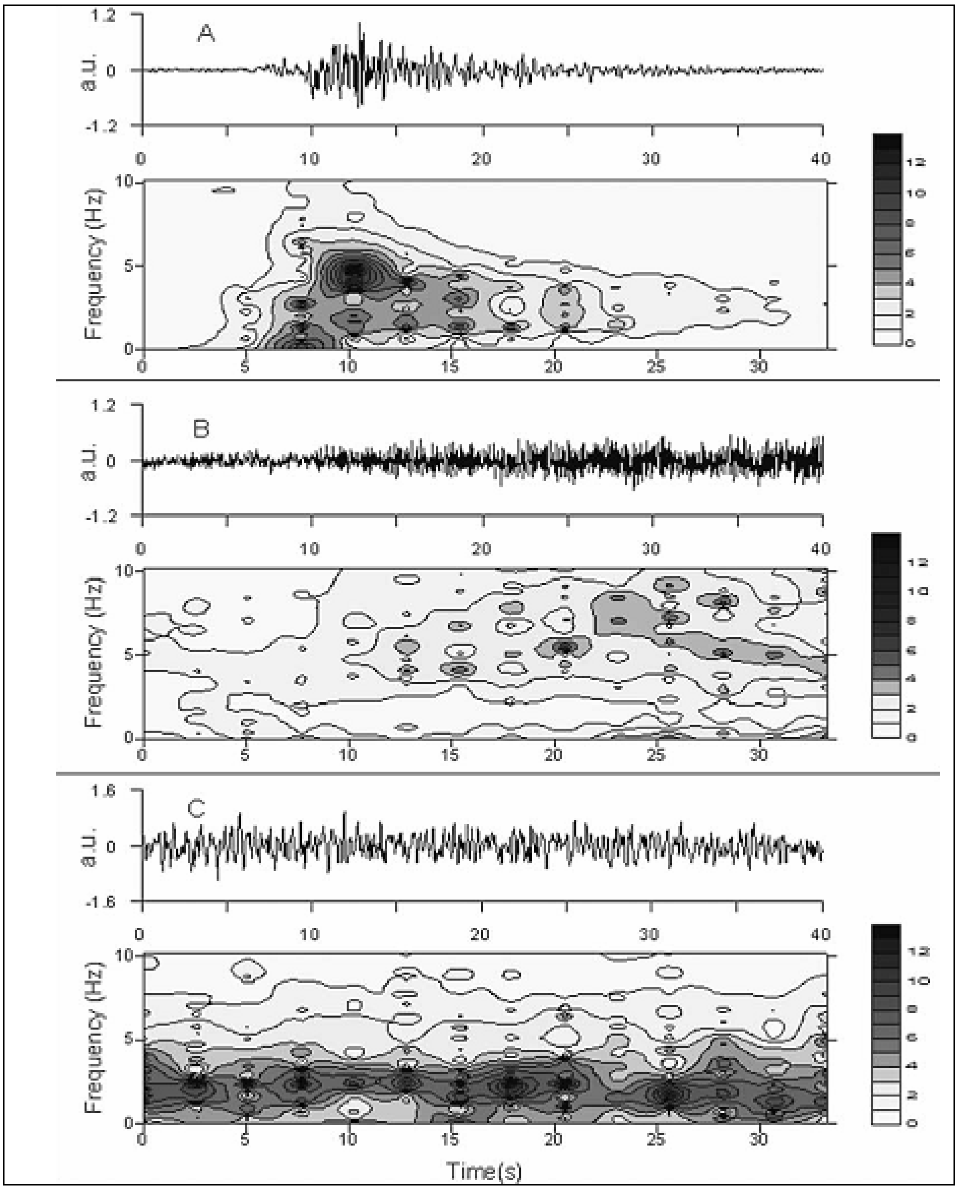

Fig. 8: Seismogram and spectrogram of Stromboli typical signals: explosion-quake (A), landslide (B) and volcanic microtremor (C).

Classification Task	Performance %
Explosion-quakes/Landslides	99.7%
Landslides/Microtremor signals	96.5%
Explosion-quakes/Microtremor signals	99.6%
Landslides/Explosion-quakes/Microtremor signals	97.2%

Table 2: Net classification performance for the Stromboli dataset.

To determine the intrinsic structure of the data and to validate the parameterization strategy used for the MLP-based classifier, we analyzed the whole dataset of explosion-quakes, landslides and volcanic microtremor signals by employing the SOM algorithm (Esposito et al, 2006 b; Giudicepietro et al, 2006). The results (Fig. 9) confirm that the unsupervised method is able to distinguish three clusters corresponding to the three classes of signals classified by the analysts, proving at the same time that the adopted parameterization strategy characterize appropriately the data.

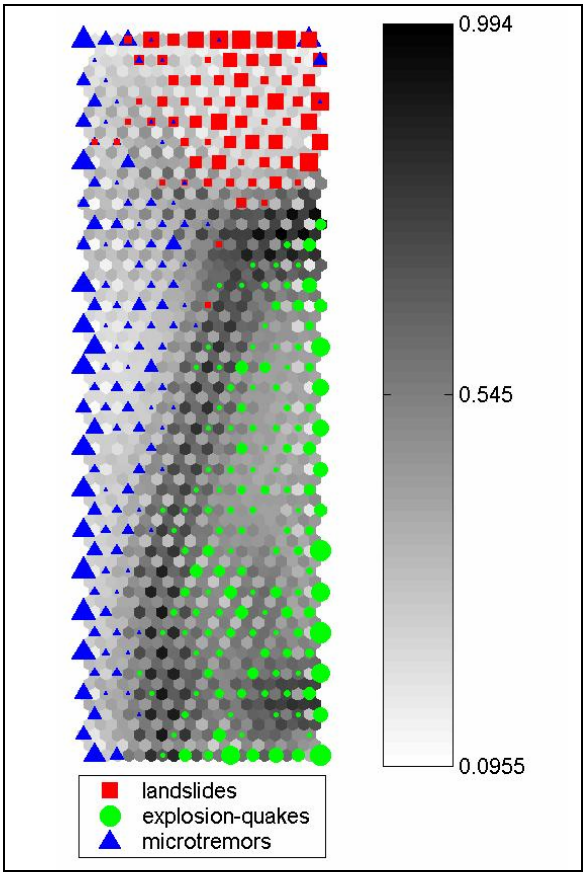

Fig. 9: The SOM map (with 396=36x11 nodes) for the Stromboli data. The node's size represents the number of the input samples in each node (the data density), while the gray coloring scale between colored symbols indicates the distances between the prototype vectors.

Moreover, thanks to the installation at Stromboli of the broadband seismometers it has been possible to observe and record *Very Long Period* events (VLP), considered an interesting phenomenon for volcano monitoring. As first approach, we have realized an unsupervised analysis and clustering of these signals through the SOM network (Esposito et al, 2006 a), in order to cluster the events on the basis of their waveform similarity, that can be useful for improving the classification task. As consecutive step we investigated the relationships between the different classes of events and the associated physical processes. Therefore, in our analysis we have considered two large datasets: the first one contains about 4000 VLP events, recorded in about one-week period, while the second one is composed of about 100000 VLP signals, recorded in a two-year period (2003-2004).

As preprocessing step, all signals have been filtered in the VLP-band (0.05-0.5 Hz) and resampled at 2Hz and normalized allowing to represent the data in a compact and meaningful way. By using this feature extraction technique input vectors correspond to seismograms and the prototypes obtained from the analysis are similar to seismograms too. This facilitates the results comprehension and aids the estimation of the neural system performance.

The SOM map and the associate prototype plot obtained for the first and the second dataset are shown in the figures 10 and 11 respectively. Observing them, we could conclude that the analysis of the VLP events in a short temporal interval, as a week, allows us to detect particular waveforms and to cluster them (Fig. 10). In a large temporal range, the analysis can be not easy due to the complexity of the volcano behavior and the resulting variety of VLP waveforms which can be much different among them (Fig. 11).

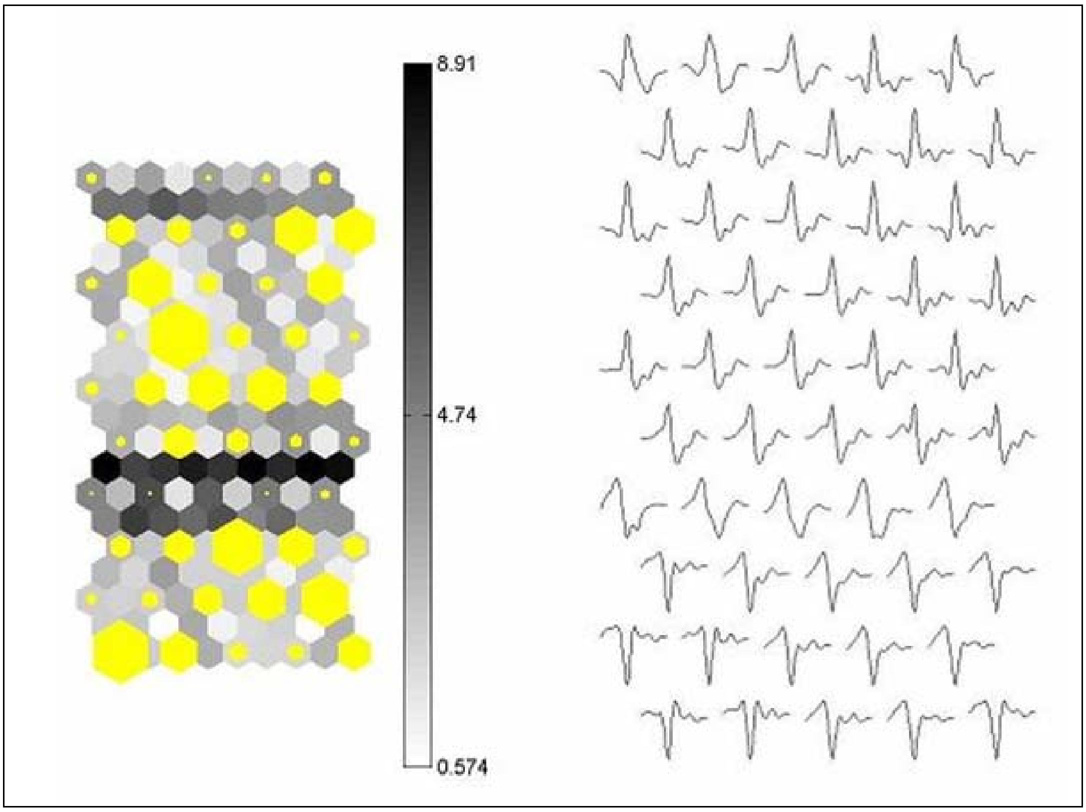

Fig. 10: The SOM map (with 50=10x5 nodes) and the associate prototypes' plot for the dataset of about 4000 VLP events.

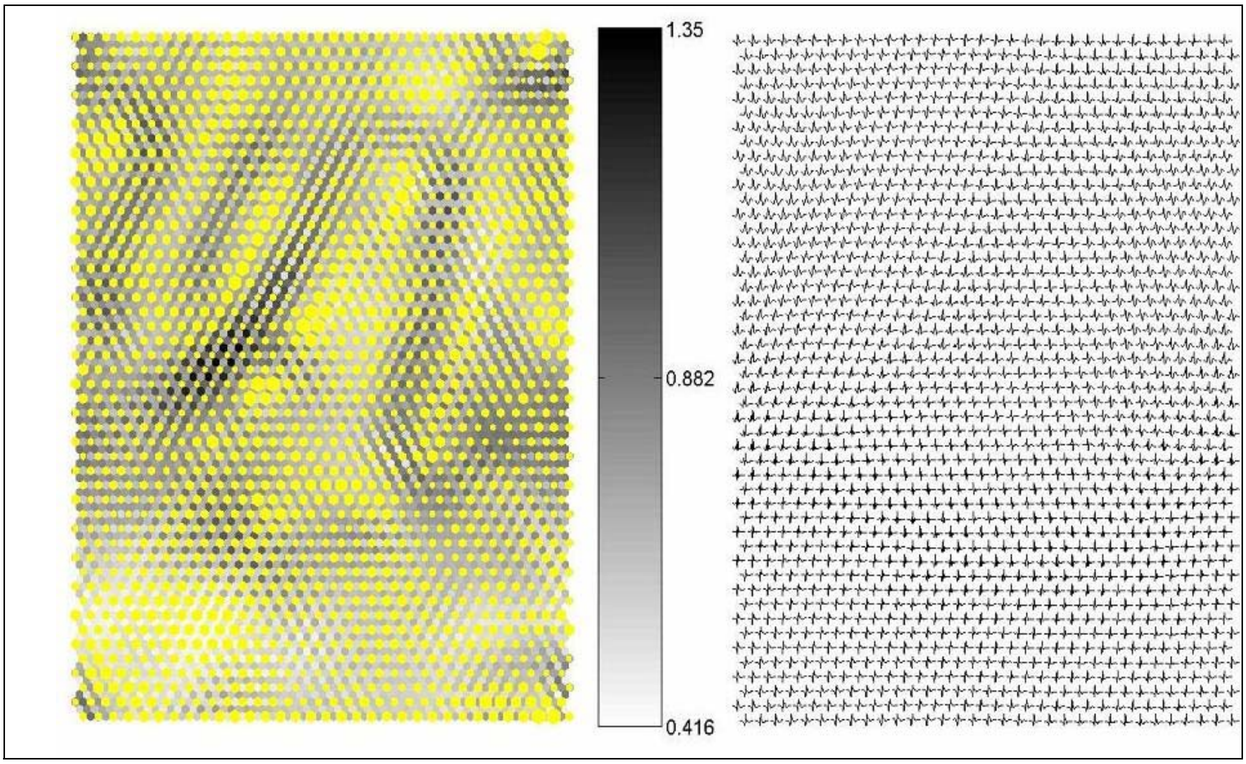

Fig. 11: The SOM map (with 48x33=1584 nodes) and the associate prototype plot for the dataset of about 100000 VLP events.

Finally, showing Stromboli an average of 200-300 explosions per day from different vents in the summit area of the cone and being the VLP events related to the explosions, it has been noted that different waveforms are often associated with different vents. Thus, we have applied the SOM algorithm to a set of 147 VLP events in order to explore the relationship between the vent producing the explosion and the associated VLP waveform (Esposito et al, 2007). These events have been recorded at Stromboli in a period between November and December 2005, when also digital infrared camera recordings were available. Therefore, from a visual inspection of the infrared camera images we have classified the VLPs on the basis of the vent producing the explosion, obtaining six vent-classes. The location of the vents is shown in a frame of the infra-red camera (Fig. 12), where the label S stay for South, N for North and C for center.

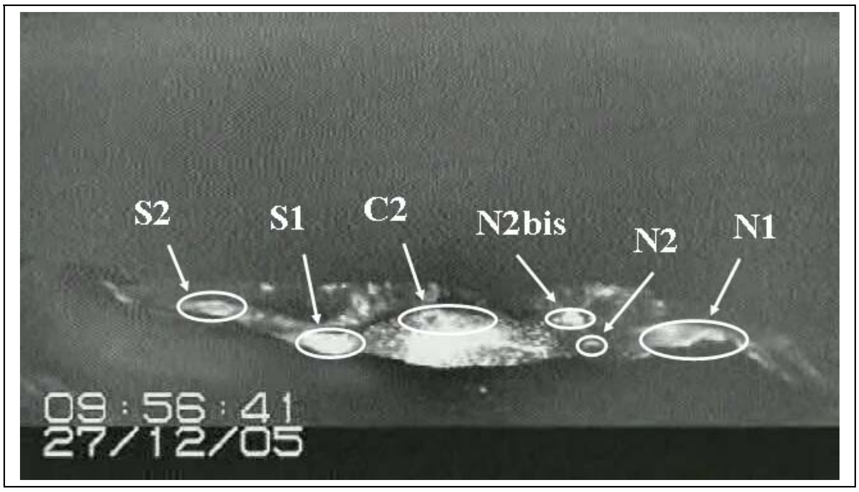

Fig. 12: The six vent-classes and their location.

For the feature extraction stage, the signals have been filtered in the VLP-frequency band (0.05-0.5 Hz), resampled at 2 samples/s and normalized obtaining a compact data representation.

Then, we clustered the VLPs applying the SOM algorithm and obtaining the map shown in figure 13.

In our analysis, three main clusters have been individuated on the map, evidenced by a thick black line in figure 13. They roughly correspond to the three main active vents in the summit area of the volcano: S2; N1; N2b. The not perfect matching between the clusters discovered by the SOM and the activity of the principal vents is due to the not systematic correspondence between the vent producing the explosion and the seismic signature of the VLP.

Actually, the most of the VLP signals associated with a given vent shows a specific waveform type, however some of them have different shapes, sometimes similar to those usually associated with an other vent.

In conclusion the SOM method correctly clustered the VLP events on the basis of their waveform similarity. Thus, as future approach, we are planning to apply this method, able to process large datasets, for the analysis and classification of the whole dataset of more than 300000 events recorded at Stromboli volcano in the last 4 years. Actually, the analysis of such a dataset can be only approached by automatic unsupervised techniques.

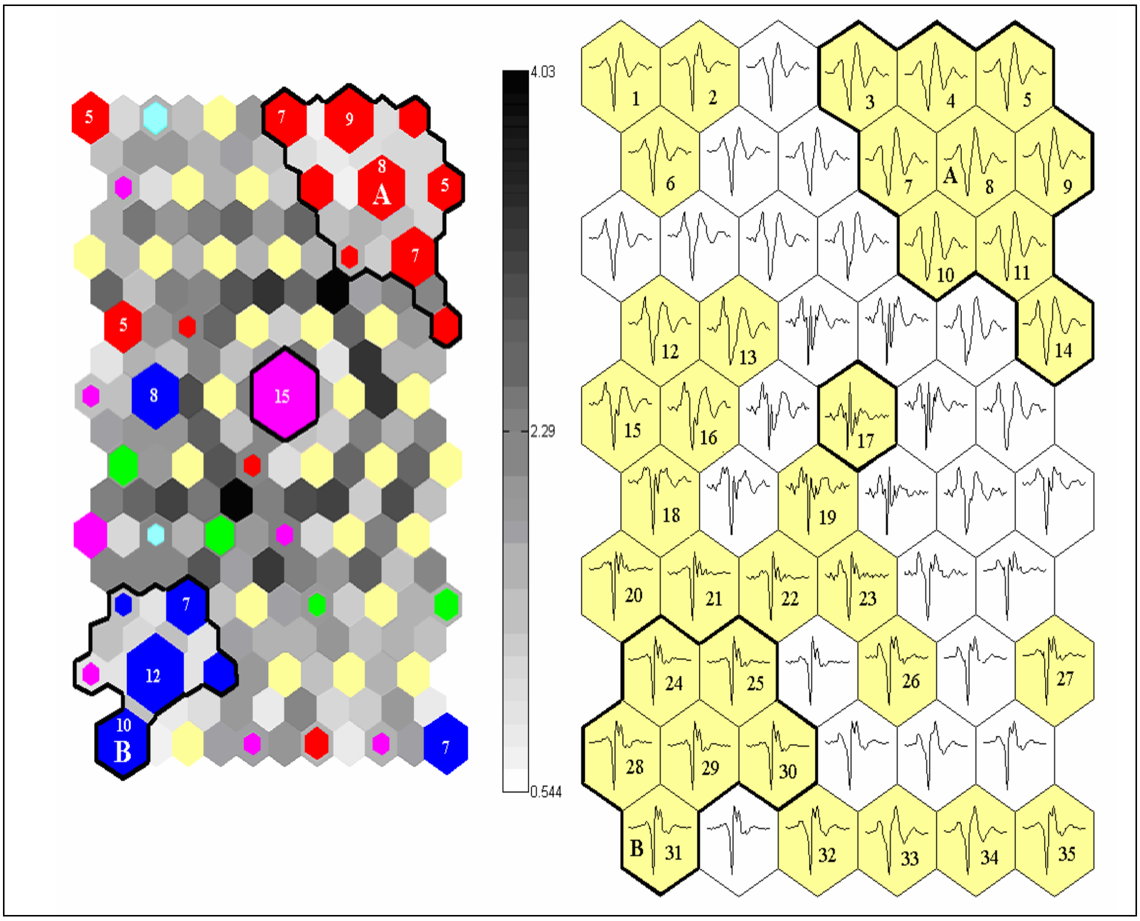

Fig. 13 : The SOM map (with 10x6=60 nodes) for the dataset of about 147 VLP events. The light yellow hexagons on the map indicate the empty nodes (zero data density). The size of the other colored hexagons represents the data density, indicated with the numerical labels for the nodes having more than 4 VLP waveforms. The gray hexagons represent the Euclidian distances between the prototypes. The different colors depict the predominant vent-class in each node: red for the S2 vent-class, blue for the N1, magenta for the N2b, green for the S1, light cyan for the N2. The prototypes corresponding to each node are shown in the right side of the plot. The white hexagons identify the nodes with zero data density (empty nodes), while the yellow hexagons show the prototypes of the nodes with one or more input signals. The thick black line on both images of the plot evidences the three main clusters identified on the map by the SOM algorithm.

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