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Neural analysis of seismic data: applications to the monitoring of Mt. Vesuvius

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ABSTRACT

The computing techniques currently available for the seismic monitoring allow advanced analysis. However, the correct event classification remains a critical aspect for the reliability of real time automatic analysis. Among the existing methods, neural networks may be considered efficient tools for detection and discrimination, and may be integrated into intelligent systems for the automatic classification of seismic events. In this work we apply an unsupervised technique for analysis and classification of seismic signals recorded in the Mt. Vesuvius area in order to improve the automatic event detection. The examined dataset contains about 1500 records divided into four typologies of events: earthquakes, landslides, artificial explosions, and "other" (any other signals not included in the previous classes). First, the Linear Predictive Coding (LPC) and a waveform parametrization have been applied to achieve a significant and compact data encoding. Then, the clustering is obtained using a Self-Organizing Map (SOM) neural network which does not require an a-priori classification of the seismic signals, groups those with similar structures, providing a simple framework for understanding the relationships between them. The resulting SOM map is separated into different areas, each one containing the events of a defined type. This means that the SOM discriminates well the four classes of seismic signals. Moreover, the system will classify a new input pattern depending on its position on the SOM map. The proposed approach can be an efficient instrument for the real time automatic analysis of seismic data, especially in the case of possible volcanic unrest.

1. Introduction

Mt. Vesuvius is one of the highest risk volcanoes in the world because of its high population density. The seismic activity is an important indicator of the state of the volcano. Thus, its variations may indicate changes in the physical state of the system and therefore can be used as tool to improve the comprehension of the dynamics of the volcano and to forecast possible eruptions [Iannaccone et al. 2001, D'Auria et al. 2013].

Currently, the seismic monitoring of the volcano is realized by a dense network of 18 stations (Figure 1), ranging from short-period, single-component, analog stations to broadband three-components digital ones. The data acquisition and transmission to the Osservatorio Vesuviano Monitoring Center is realized through different systems such as UHF, Wi-Fi radio links, and TCP/IP client-server applications [Giudicepietro et al. 2010, Orazi et al. 2013].

The signals usually recorded by the seismic network are earthquakes, landslides and transient signals produced by artificial explosions in quarry and undersea. Other types of signals, such as regional and teleseismic earthquakes, are also recorded, but in this work we take into account only the local seismicity. A new class of signals, defined as "other", has been added in our analysis. It includes all the events, such as thunders, that do not fall in the previous classes but which is still important to recognize, to improve the monitoring of Mt. Vesuvius.

Generally, the detection and discrimination of the recorded events is performed by human experts through procedures based on the visual analysis of their spectral and temporal features [Masiello et al. 2005, Esposito et al. 2007]. To automate this process and reduce the false detection of events generated by natural and artificial sources, we propose an unsupervised approach based on neural networks that should allow the discovery of the intrinsic structure of data and group similar events.

Neural networks are computational models inspired to the human brain functioning and, like it, are able to learn from examples adapting themselves to changes in the external environment. They have been widely applied in different fields from engineering sciences to medicine, biology and economics. Good results have also been obtained in volcanic seismology: for classifying different seismic signals, such as rockfalls, hybrids, long-period events, VT events, and regional events, recorded at Soufrière Hills [Langer et al. 2006]; for estimating the activity state of the volcano Etna by identifying different characteristics in the continuous background signal [Langer et al. 2009]; for monitoring long-term variations and short-term transients at Mount Merapi volcano [Köhler et al. 2010]. Neural networks have also been applied to realize an automatic system for the discrimination and detection of the landslides recorded on Stromboli volcano [Esposito et al. 2006, 2011].

In addition to neural networks, other approaches are available in literature for the discrimination of seismic signals. For example, Hammer et al. [2012] suggest a classification procedure based on Hidden Markov Models (HMMs) for volcano rapid-response systems applied to a dataset recorded at Soufrière Hills volcano.

Neural networks are mainly classified on the basis of the learning process as supervised or unsupervised. In the first case, a previously labeled dataset is necessary to train the net, where to each input pattern is associated the correct expected answer. In Scarpetta et al. [2005], a supervised discrimination system based on a Multilayer Perceptron (MLP) [Bishop 1995] has been proposed. However, an unsupervised procedure based on a SOM net [Kohonen 1995] could be more effective when no *a-priori* data classification is available but it is required that the neural algorithm applies a similarity measure to cluster the data [Masiello et al. 2005, Giudicepietro et al. 2008]. In addition, as we shall see, the unsupervised system is able to classify new input signals on the basis of their position on the SOM map.

In the following, we describe the Mt. Vesuvius dataset and the applied preprocessing techniques. Then we introduce the SOM technique and illustrate its results.

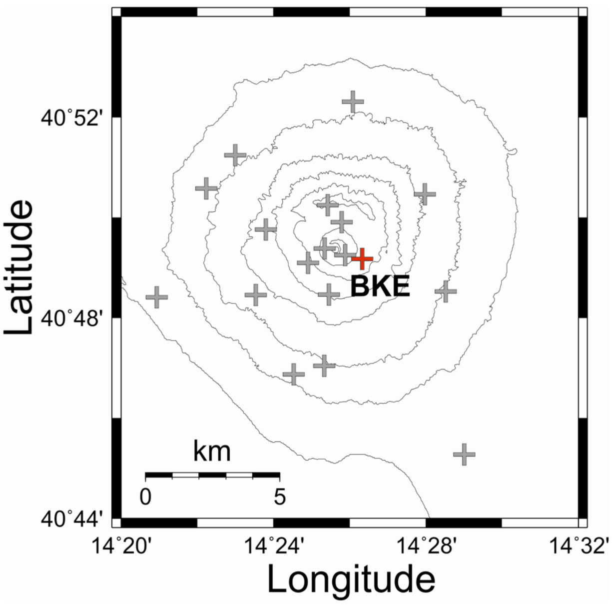

Figure 1. Map of the monitoring seismic network of Mt. Vesuvius. The position of the BKE station, whose data have been used in this work, is shown by the red cross.

2. The Mt. Vesuvius dataset

The examined dataset consists of 1499 files classified by the expert seismologists into four typologies of events:
– 259 earthquakes,
– 545 landslides,
– 412 artificial explosions (quarry and sea),
– 283 events of the class "other".

The signal files have been extracted from the seismological database of the Osservatorio Vesuviano (Istituto Nazionale di Geofisica e Vulcanologia) [D'Auria et al. 2008]. The temporal range covered by the events runs from January 1, 2007, to December 31, 2011. We have considered in particular the seismic data of the BKE station (vertical component) (Figure 1) which is located very close to Mt. Vesuvius crater, thus recording even the smallest and shallowest earthquakes [Giudicepietro et al. 2010, D'Auria et al. 2013]. In our analysis, we have not considered recordings showing evident anomalies such as spikes, double events, clipped waveforms.

In Figure 2 the 22s time windows showing the seismograms (top panels) and the corresponding spectrograms (bottom panels) of some events representative of the four classes are depicted. All the events of the earthquake class (Figure 2A) have a magnitude higher than 0.9 and they are indicated as volcano-tectonic (VT). For this class the signal shows an impulsive onset and the typical frequency range content of a local VT earthquake, with a peak at about 15 Hz. The signals associated to small landslides and rockslides (Figure 2B), occurring mostly within the Vesuvius crater, have usually a spectral content in the range of 5-20 Hz.

The class of artificial events includes both quarry blast and undersea explosions in the Gulf of Naples. The signal associated to a quarry blast (Figure 2C) is characterized by a broad spectrum between 5 and 25 Hz. The spectrum of an undersea explosion (Figure 2D) presents, instead, two distinct spectral components: the initial part of the signal, related to the seismic component, has a spectral content in range of 10-20 Hz; while the second one, associated to the hydroacoustic component of the wavefield, shows a spectral content mostly below 10 Hz.

Finally, the class "other" contains all the other events recorded by the monitoring network in the Mt. Vesuvius area which do not belong to the previous classes. For this class, the transient in Figure 2E is characterized mainly by a spectral peak at about 15 Hz, superimposed to a background signal with a spectrum mostly below 5 Hz. The signal in Figure 2F shows a spectral content of an another type of signal belonging to the same class. This last was subsequently identified as a thunder signal and is characterized by a spectrum mostly limited to the range 12-18 Hz.

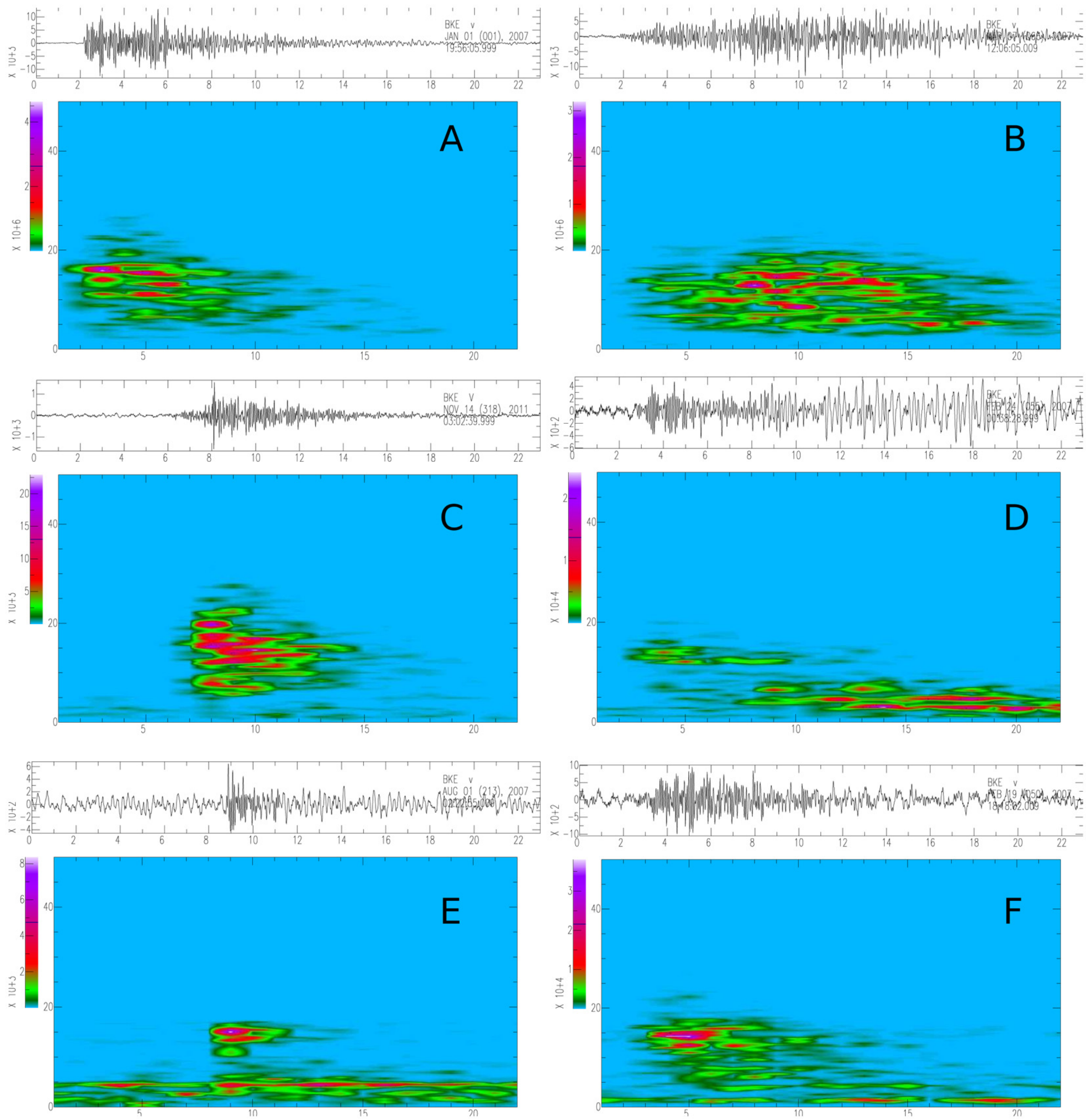

Figure 2. The 22s time windows show the seismograms (top panels) and the corresponding spectrograms (bottom panels) of the signals representative of the four classes of events: an earthquake (A), a landslide (B), a quarry blast (C), an undersea explosion (D), a not classified event (E) and a thunder signal (F), both belonging to the class "other".

To perform the unsupervised analysis we have used records of 2200 samples (i.e. 22s with a sampling rate of 100 Hz). The event onset has been detected using a manual picking for all the signals of the four classes. Each seismogram contains a 1s-long pre-event with respect to the onset.

3. Dataset preprocessing

To obtain a good clustering, methods of extraction of the information most significant and representative of the events have been applied to the dataset. In our case the Linear Predictive Coding (LPC) technique [Makhoul 1975] and a discrete waveform parametrization were used to extract the spectral features and to preserve the temporal information respectively. Moreover, in this way a reduction of the size of the patterns has been realized providing a compact representation of the seismic signals.

The LPC algorithm works by modeling each signal sample s_n as a linear combination of its previous p values as described below:

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

where c_k are the prediction coefficients and G is the gain. The parameter p represents the model order and it is problem-dependent. An optimization procedure

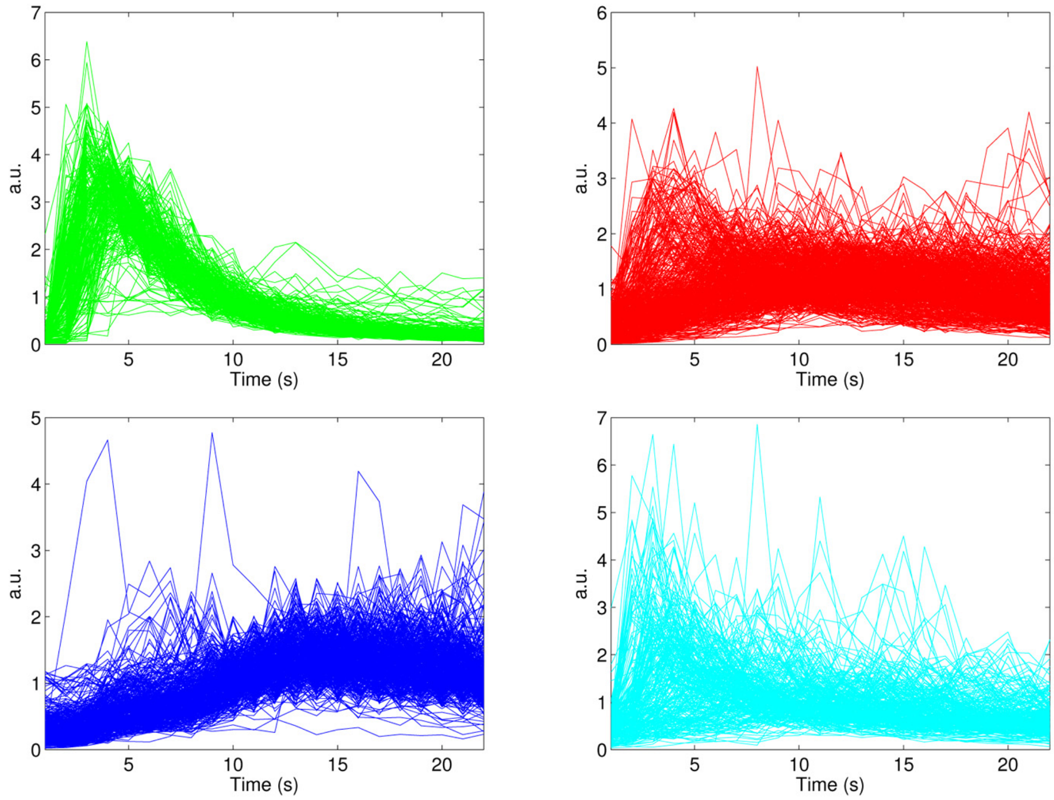

Figure 3. Envelopes in the time domain for all the signals of each of the four classes of events: green for earthquakes, red for landslides, blue for artificial explosions and cyan for events of the class "other".

evaluates the c_k estimation minimizing the error between the true value of the signal sample and its LPC estimate. The prediction coefficients efficiently encode the signal frequency features.

In our case, each record was processed dividing it in 15 analysis windows of 2.56s duration and 1.28s overlapping, and extracting $p = 10$ LPC coefficients from each of them plus the gain, as a good compromise in maximizing the representation compression and minimizing the corresponding error.

The temporal characteristics of the signals are provided through a discrete waveform parametrization calculated as the properly normalized difference between the maximum and the minimum signal amplitude in a 1s long analysis window and added to the data representation. In Figure 3 the envelopes of all signals for the four classes are plotted: green for earthquakes, red for landslides, blue for the artificial explosions and cyan for the events of the class "other". Observing these images, it is possible to note how the temporal information contributes significantly in discriminating between the earthquakes, the landslides and the artificial explosions, while between the landslides and the events of the class "other" there is a less sharp separation.

At the end of the preprocessing, each initial signal file of 2200 samples is encoded by a vector of 187 features (165 spectral coefficients and 22 time components). As final step, the variance of the resulting vectors was normalized to one since this improves the SOM clustering [Esposito et al. 2007].

4. The SOM technique

Among the available unsupervised methods of cluster analysis [Everitt et al. 2001], the SOM technique [Kohonen 1995, Kohonen et al. 1996] has been exploited in many works [Masiello et al. 2005, Esposito et al. 2006, Esposito et al. 2007, Esposito et al. 2008, Langer et al. 2009, Köhler et al. 2010]. It has many advantages: 1) it does not have strong dependencies by its parameters; 2) it does not require assumptions about the similarity measure to be taken into account to group the data because it is able to detect isolate patterns and structures in the data; and 3) it allows an easy visualization and interpretation of the results.

A SOM network is composed by a set of neurons or nodes organized on a grid, usually bi-dimensional. A weight vector, called prototype vector or codebook vector, with size equal to that of the input vector, is associated to each neuron. The neurons are connected to adjacent ones by a neighbourhood relationship that characterizes the map topology or structure. This latter provides information about the local lattice structure (which can be rectangular or hexagonal), and the global map shape (sheet, cylinder or toroid). The number of neurons, which also corresponds to the number of prototypes and that defines the size of the grid, is usually chosen as big as possible in order to preserve the smoothness and generalization of the mapping. However, at the same time, it is necessary to consider that the training phase with a large number of neurons becomes computationally unmanageable for many applications. In our case the SOM parameter values were chosen according to Kohonen et al. [1996] and the SOM Toolbox for Matlab (http://www.cis.hut.fi/somtoolbox/). Thus, we used the default number of neurons equal to 5 * sqrt(n) where n is the number of training samples, while the map grid sidelengths are determined by the ratio between eigenvalues of the training data. Before the training the prototypes are initialized with small random values (initialization step). Other kinds of initializations are possible, as suggested in Kohonen et al. [1996], but the random initialization was originally selected to prove the self-organizing capability of the SOM also when starting from an unordered condition.

Therefore, the SOM algorithm [Kohonen 1997] performs a non-linear mapping from an high-dimensional input space into a bi-dimensional grid of processing units. Through a competitive learning, at each iteration it identifies the winning node for each input, i.e. the unit whose connection weights are the closest to the input pattern in terms of Euclidean distance. Then it updates its weights and those of the adjacent nodes (for mathematical details refer to Kohonen [1995]). In this way the resulting map preserves a local spatial ordering of original data such that similar inputs fall in topographically close nodes.

Thus, the SOM can be applied as a clustering and projection method since it provides a good representation of the cluster structure, showing on the map both the data density and the Euclidean distances among prototypes, and permits a simple and immediate comprehension of the results.

5. The SOM results

The SOM map obtained for the considered dataset is illustrated in Figure 4. It has 16 × 12 = 192 units and presents a local hexagonal structure and a global toroidal shape, where the sides of the map (upper and lower and the lateral ones) are connected to each other in order to avoid the problem of the border effects [Andreu et al. 1996]. The toroidal shape is however shown as sheet to better visualize the clusters and to facilitate the interpretation of the results.

Each node of the map, depicted as a yellow hexagon, represents a cluster of data and its size indicates the number of signals that fall into that node, i.e. the density. The separation between the clusters is given

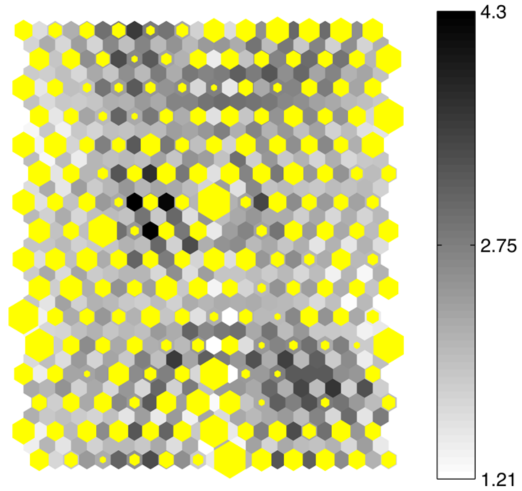

Figure 4. The toroid SOM map with 192 (16 × 12) nodes obtained for the Vesuvius dataset: each yellow hexagon indicates a cluster of data and its size represents the number of signals which fall in it. The gray hexagons specify the Euclidean distances between the prototypes and so between the feature vectors according to the gray level scale shown on the right. The toroidal shape, in which the lower and upper edges and the left and right sides are joined, is displayed as sheet to facilitate the cluster visualization.

by the Euclidean distance represented on the map as gray hexagons using a gray level scale [Kohonen 1995, Kohonen et al. 1996]. In this way dark gray color corresponds to large distances between the prototypes, meaning that they and the associated feature vectors are very different.

As preliminary post-processing analysis, to achieve a first validation of the SOM results that highlights a possible relationship between the examined classes of signals and the obtained unsupervised clustering, we have plotted on the initial map of the Figure 4 the la-

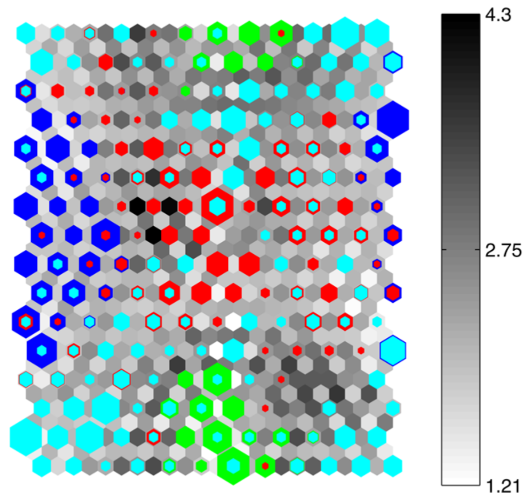

Figure 5. The toroid SOM map with the labeling of the events realized by the experts: green for the earthquake class, red for the landslide class, blue for the artificial explosion class and cyan for the class "other". The hexagons with color overlap indicate the nodes in which fall signals belonging to different classes.

beling of the events made by the human experts, achieving the Figure 5. The different colors of the hexagons indicate the four different classes of events: green for earthquakes, red for landslides, blue for artificial explosions and cyan for signals of the class "other". Color overlaps mean that different types of signals belonging to different classes fall in the same node. However, despite the possible overlaps, we can assert that each class of events is mainly clustered in a specific region of the map. This is more clear observing Figure 6 where the individual SOM maps with the labelling of the experts for each of the four classes are plotted separately on the initial SOM map displayed in Figure 4. Thus, earthquakes (green) are placed on the upper and lower region of the SOM; artificial explosions (blue) are on the left and right edges; the landslides (red) are instead localized mainly in the central area of the map; finally, the signals of the class "other" (cyan) are distributed in a complementary way with respect to landslides.

About the performance of the proposed method, while for the supervised MLP network applied by Scarpetta et al. [2005] a percentage of correct classification is defined to evaluate the quality of the results, generally for the SOM network this latter is not defined and only a post-processing analysis can provide information on the effectiveness of the technique. For example, the human expert knowledge can be used to interpret the results and reveal which cluster corresponds to a particular class [Köhler et al. 2010]. However, the advantage of an unsupervised technique as the SOM is to allow to deal with large datasets also not previously labeled by the experts. Furthermore, the network training is entirely data-driven, no target vectors for the input patterns are required and finally it enables to group the input data finding their intrinsic features.

Finally, we can affirm that in our case the clustering performed by the SOM separates well enough the four classes of signals defined by the experts.

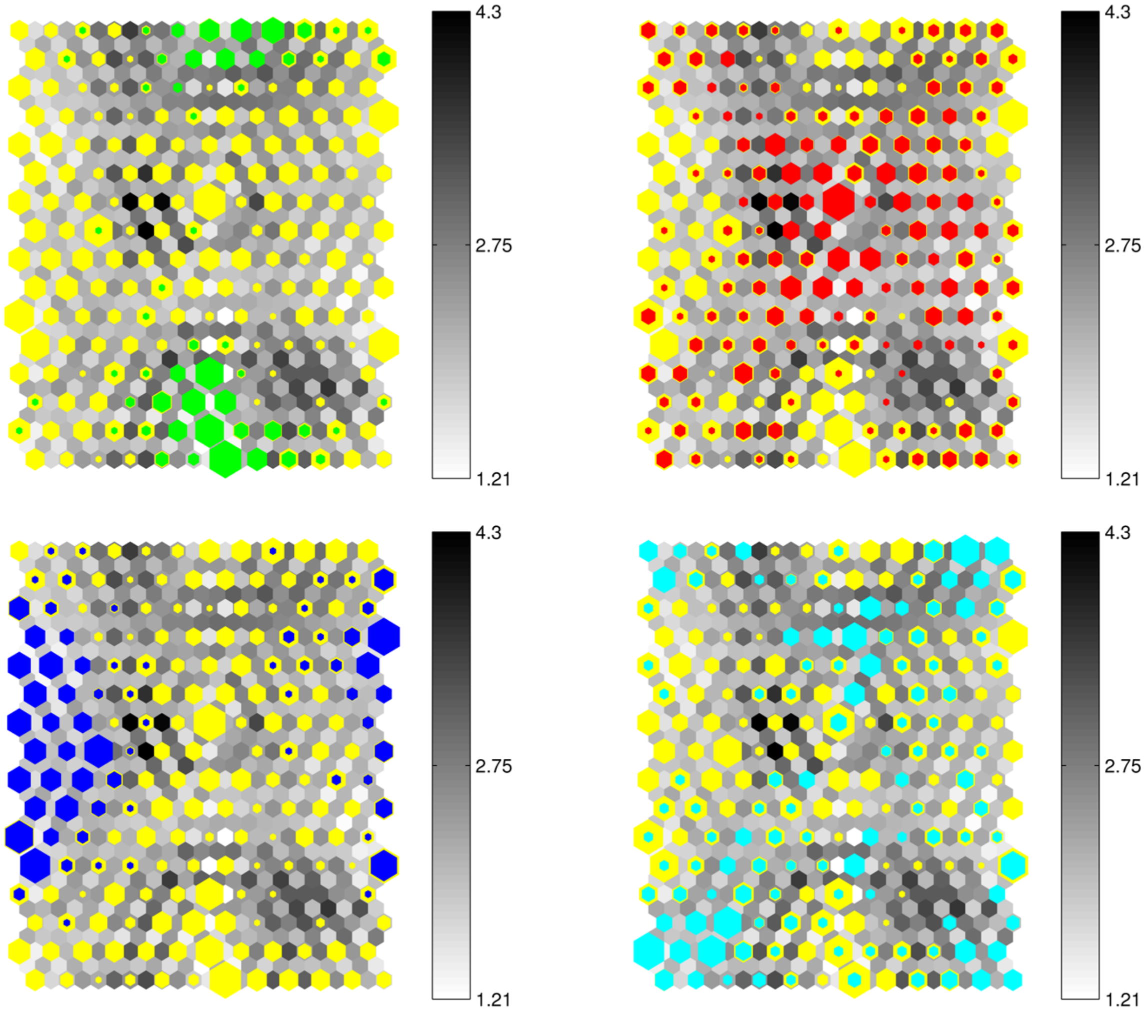

Figure 6. The individual SOM maps with the labeling of the experts for each of the four classes are displayed: green for the earthquake class, red for the landslide class, blue for the artificial explosion class and cyan for the class "other". It is possible to note the different positions on the map of the four types of examined events.

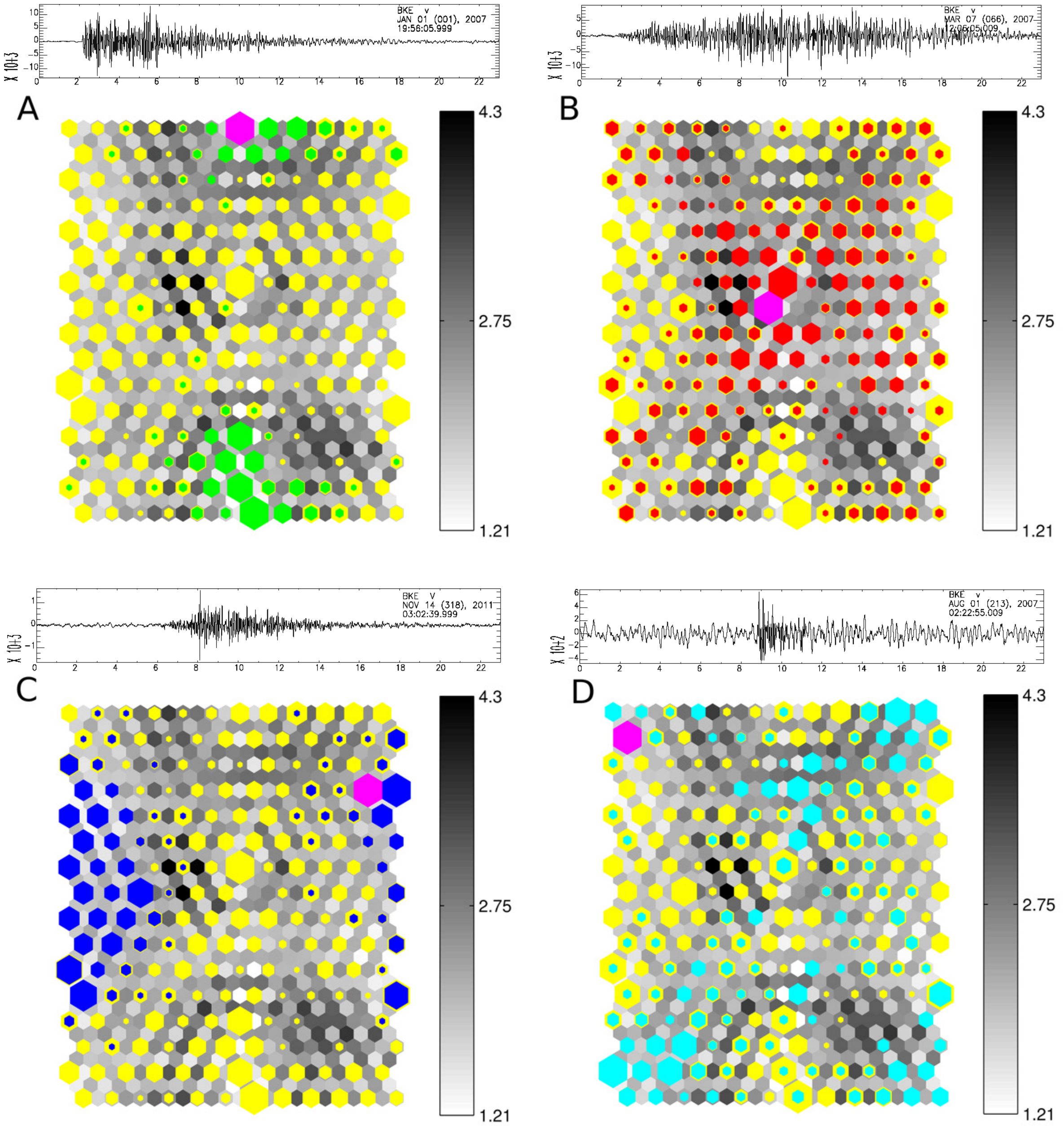

Figure 7. Seismograms of some signals of the dataset and their position on the SOM map. The purple hexagon indicates each time the different examined event: an earthquake in A, a landslide in B, a quarry explosion in C, and finally an event of the class "other" in D. Its position lies each time in a different region of the map which corresponds one of the four classes: earthquakes (green), landslides (red), artificial explosions (blue) and "other" (cyan).

6. Conclusions

In the previous section the SOM network has been applied on a dataset of seismic events recorded in the Mt. Vesuvius area and represented through a 187-feature vectors encoding both spectral and time information. The aim was to realize an unsupervised clustering of these signals using a projection technique able to identify and visualize at the same time on a bi-dimensional plane the hidden structure of the data. This can be helpful to the experts for the automatic detection and classification of the events under examination. In particular, being unsupervised, the neural system allows to identify a position on the map for each new input signal which corresponds to one of the predefined classes and therefore to provide a possible classification of this event.

For this purpose, Figure 7 shows the seismograms of some events and their positions in different regions of the map corresponding to the four classes of signals. The purple hexagon indicates each time the examined signal: in A it refers to an earthquake and its position falls in the green area of the earthquakes class; in B it indicates a landslide and it lies in the red region of the landslides class; in C it is a quarry explosion and its location is in the blue zone of the artificial explosions class; finally, in D it represents an event of the class "other" and it is located in the cyan area of that class. About the class of the artificial explosions in quarry and undersea, we can observe that there is not a clear distinction between these two types of events on the map (Figure 7, blue area), although their spectrogram and waveform appear quite different (see Figure 2C,D). Even if the discrimination between these two subsets of the same class is outside from the aims of this work, we can assume that this probably happens because there is not a sufficiently representative number of sample patterns for them.

Although our work takes into account only events related to the local seismicity of Mt. Vesuvius, new types of events and then new classes of signals may be added dynamically to the SOM for a real-time analysis. Thus, the advantage of the unsupervised neural system is that it can give an answer also for unknown event types indicating the specific class where they fall on the basis of their position on the map and so allowing their classification. This system has shown also a high potential for real-time applications devoted to the discrimination of automatically detected signals. Moreover, it could also provide a valuable tool for the automatic classification of seismo-volcanic signals (long-period events, volcanic tremor, etc.) which usually are characterized by a variety of waveforms.

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