

Chapter 2

A Neural Approach for Hybrid Events Discrimination at Stromboli Volcano

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Abstract Stromboli volcano is considered one of the most active volcanoes in the world. During its effusive phases, it is possible to record a particular typology of events named “hybrid events”, that rarely are observed in the daily volcano activity. These ones are often associated to fault failure in the volcanic edifice due to magma movement and/or pressurization. Their identification, analysis and location can improve the volcano eruptive process comprehension. However, it is not easy to distinguish them from the other usually recorded events, i.e. explosion-quakes, through a visual seismogram analysis. Thus, we present an automatic supervised procedure, based on a Multi-layer Perceptron (MLP) neural network, to identify and discriminate them from the explosions-quakes. The data are encoded by using LPC coefficients and then adding to this coding waveform features. The 99% of accuracy was reached when waveform features are coded together with LPC coefficients as input to the network, emphasizing the importance of temporal features for discriminating hybrid events from explosion-quakes. The results allow us to assert that the proposed neural strategy can be included in a more complex automatic system for the monitoring of Stromboli volcano and of other volcanoes in the world.

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2.1 Introduction

The volcanic activity of Stromboli, one of the most active volcanoes in the world, is described by small to medium size explosions occurring at the eruptive vents on the top of the volcano [11]. Usually, the explosion frequency rate ranges between 6 and 18 events per hour [4, 5]. This persistent eruptive activity is sometimes interrupted by effusive phases which lead to the formation of lava flows on the Sciara del Fuoco, the NW flank of the volcano characterized by lateral collapse structures [16]. In recent decades, two major effusive phases occurred in 2002–2003 [3] and 2007 [24], after which the scientific community and civil protection authorities made a big effort to improve the monitoring [6] and knowledge of Stromboli volcano dynamics [1, 18]. Also the landslides, which caused the tsunami of 2002 [21, 26–28] and were precursors of the effusive phase on February, 2007 [24], were investigated, in particular their detection and discrimination has been exploited by using neural networks [8–10, 17]. Some minor episodes of lava overflow from the summit craters occurred in later years [14].

Also hybrid events, typically recorded during Stromboli effusive phases, can be considered significant signals as they provide important information on the volcano status. Their sources are usually very shallow [12, 22]. Esposito et al. [12] suggested a relationship between the formation of a fracture system at the summit of the volcano (6–8 March, 2007) and the source of the hybrid events, recorded as swarms in that period and located in the same position. Hybrid event waveforms are hardly distinguishable from those of explosion-quakes which are characteristic of the Stromboli wave-field. Thus, we propose an automatic system, based on a Multi-Layer Perceptron network, to discriminate hybrid signals from the explosion-quakes. In the following we introduce the seismic signals recorded at Stromboli volcano, explain the parametrization chosen for the data encoding, illustrate the adopted neural strategy, describe the MLP results and finally present our conclusions.

2.2 Seismic Signals at Stromboli Volcano

The semi-persistent explosive activity of the Stromboli volcano produces the typical explosion-quake signals (Fig. 2.1). The monitoring seismic network also records regional and teleseismic earthquakes, which occur at a great distance from the island, and local seismic transients due to volcano-tectonic events or landslides. However, they are not investigated at this time.

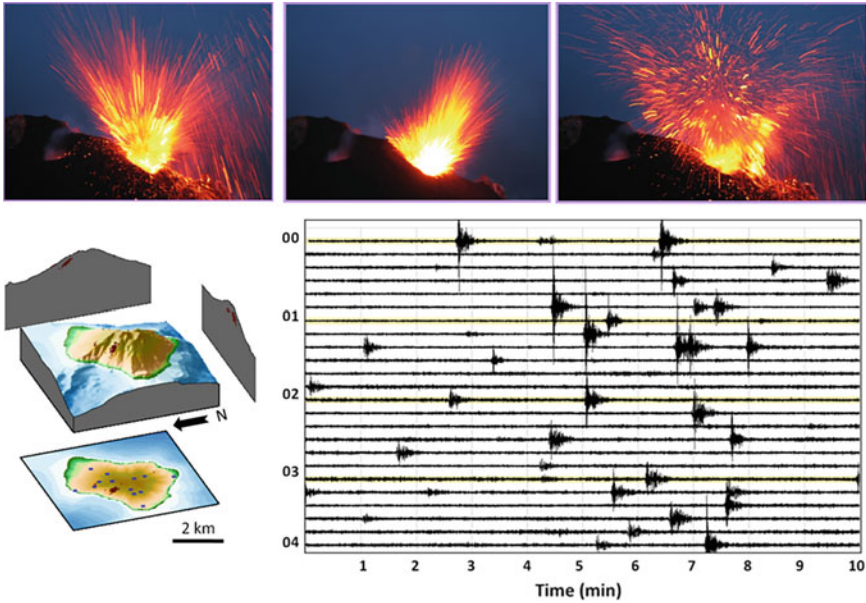


Fig. 2.1 Examples of explosion-quakes at Stromboli volcano: the first three panels are photos of explosion-quakes (courtesy of Rosario Peluso). Below, on the *right*, a 4-hour long recording window of powerful explosion-quakes is depicted; while on the *left* the explosion-quake location on the map of Stromboli island is visualized (small *red points*)

Hybrid events are also recorded, generally during volcano effusive phases and rarely during its usual explosive activity. They can be considered a particular typology of seismic events observed at several volcanoes. The left panel of Fig. 2.2 shows the location, with the geometry of the seismic network, of some hybrid events recorded during the swarm occurred on March 6–8, 2007, while on the right their representation on the seismogram is depicted.

The aim of this work is to discriminate hybrid events from explosion-quakes, since they are not easily distinguishable only through a visual analysis of their seismograms. Figure 2.3 shows, on the top panel, the seismograms of an hybrid event (on the left) and of an explosion-quake (on the right) and their corresponding spectrograms in the frequency domain, on the bottom panel. As observed in the figure, the hybrid event (on the left) presents an initial part with a high frequency content and a second part with a narrow frequency band, while the explosion-quake signal (on the right) exhibits no distinct seismic phases and has a frequency range of 1–6 Hz.

Observing the hypocenters of the events of 6–8 March 2007 swarm (Fig. 2.2), we can see that they are concentrated near the volcano surface, at an elevation raging between 600–800 m a.s.l., indicating a shallow source of these signals. In the same period, the formation of a fracture system at the summit of the volcano was observed (Fig. 2.4).

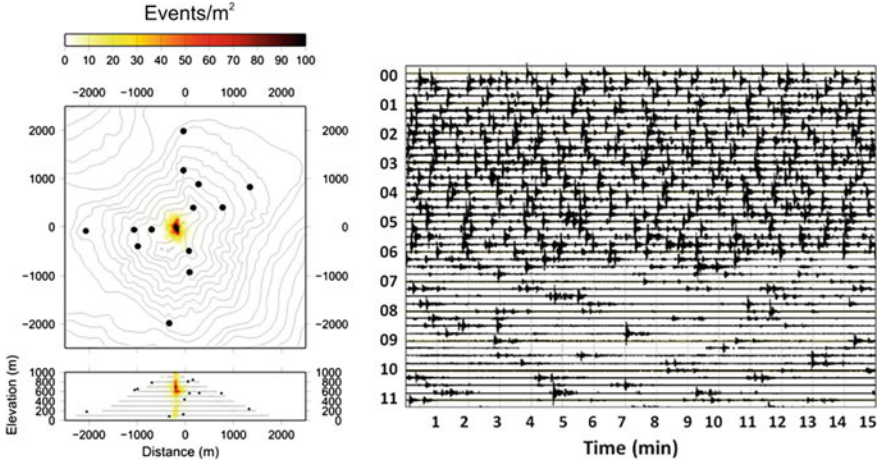


Fig. 2.2 A temporal window of the swarm of hybrid events recorded during March 6–8, 2007, on the *right*, and the relative location of some of them, on the *left* (after Longobardi et al. 2012). The *black points* in the *left panel* indicate the 13 seismic stations of Stromboli monitoring network

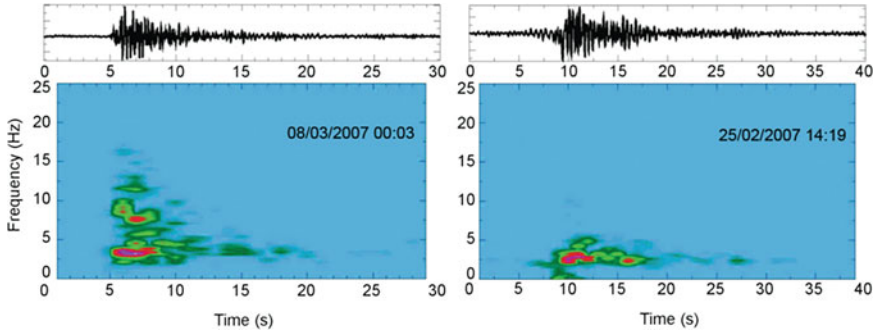


Fig. 2.3 The waveforms and the associated spectrograms of an hybrid event (on the *left*) and of an explosion-quakes (on the *right*)

2.3 Data Parametrization

The exploited dataset is of 884 events partitioned into two classes, i.e. 455 hybrid events and 429 explosion-quakes. For both classes each record has a duration of 18 s i.e. a vector of 900 samples with a sampling frequency of 50 Hz.

In order to obtain a significant and discriminating data encoding, the following plots of the signals have been performed and analyzed: the Amplitude v/s Time plot (Fig. 2.5), the LPC [20, 23] Spectrum (Fig. 2.6) and the Spectrograms (Fig. 2.7) both for an explosion-quake (on the left) that for an hybrid event (on the right) respectively.

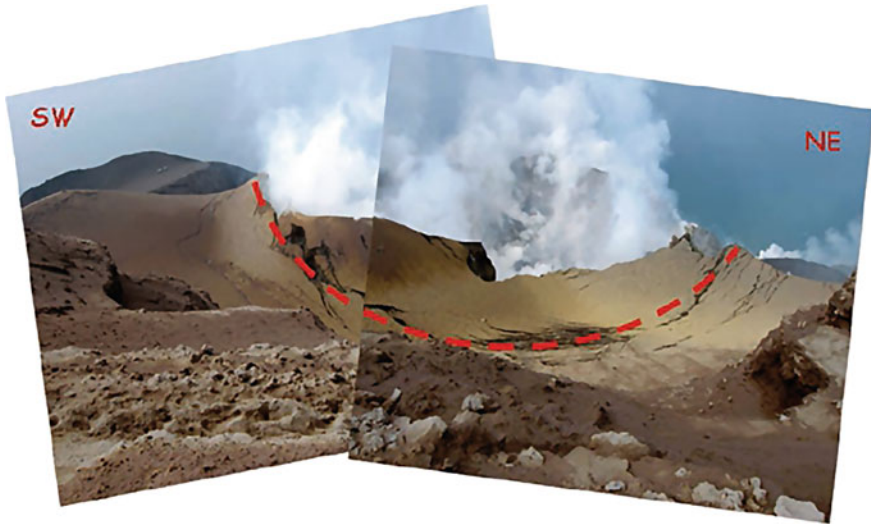


Fig. 2.4 The fracture system at the crater terrace of Stromboli during the 2007 effusive phase highlighted by the *red dashed line* (photo by Tullio Ricci)

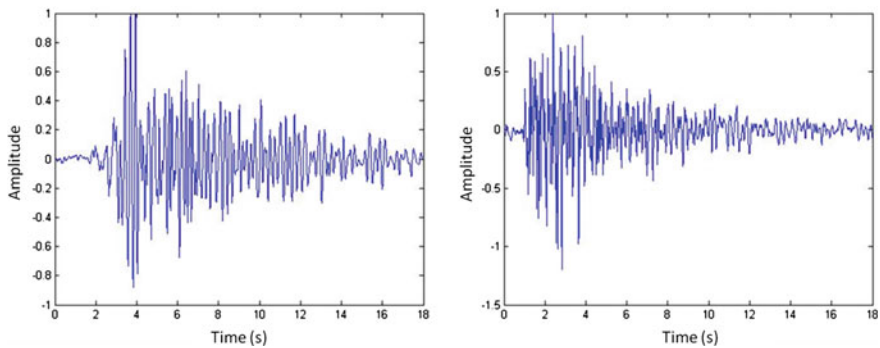


Fig. 2.5 The amplitude v/s time plot of an explosion-quake (on the *left*) and of a hybrid event (on the *right*) respectively

From the above plots we can infer the following observations: first, the LPC spectra of the explosion-quake (Fig. 2.6) shows some peaks and then a sudden and consistent decrease; on the contrary, that of the hybrid event presents clear peaks with no sudden decline. Second, looking at the spectrograms (Fig. 2.7), peaks of amplitude are observed at low frequency for the explosion-quake, whereas at the beginning of the hybrid event we can observe high frequency peaks. The same can be noticed from the seismograms (Fig. 2.5). These remarks led us to use a data representation that considers not only the LPC [20, 23] coefficients, but also the waveform information obtained as:

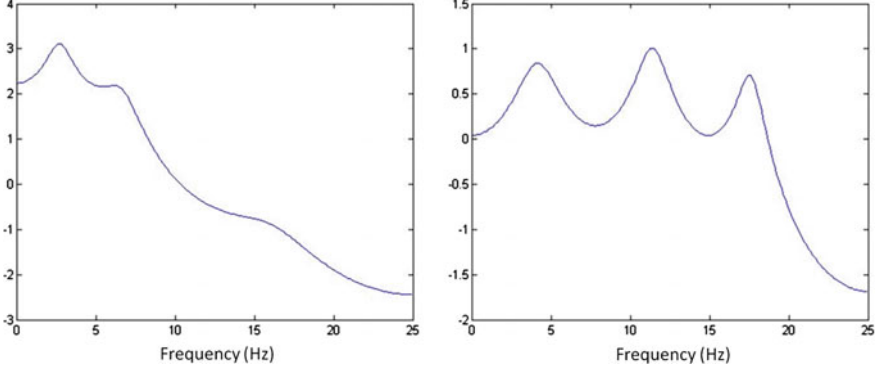


Fig. 2.6 The LPC spectrum of an explosion-quake (on the *left*) and of a hybrid event (on the *right*) respectively

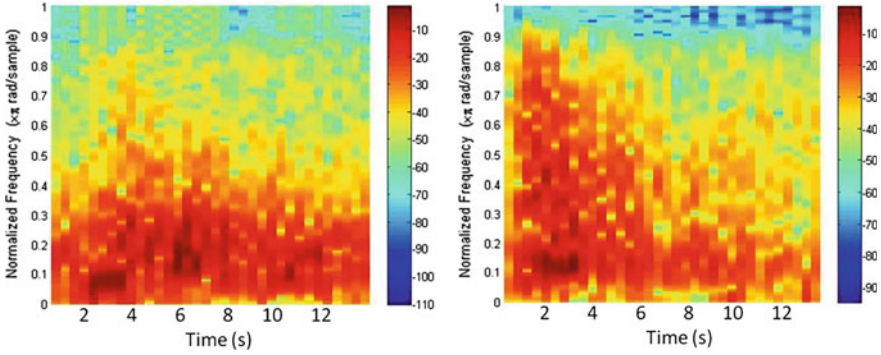


Fig. 2.7 The spectrograms of an explosion-quake (on the *left*) and of a hybrid event (on the *right*) respectively

$$W_i = (S_{imax} - S_{imin}) * N / \Sigma (S_{imax} - S_{imin}) \quad (1)$$

where:

- S_{imax} = is the maximum value in the i -th window,
- S_{imin} = is the minimum value in the i -th window,
- N = is the number of windows

We use a window length of 90 samples (i.e. 1.8 s). Figure 2.8 visualizes the waveform coefficients plotted in the mid-point of time windows for an explosion-quake signal.

At the end of the preprocessing stage, each signal will be encoded by a vector of LPC and waveform coefficients. The number of coefficients was not fixed in order to test different representation and select the best one.

Fig. 2.8 The waveform coefficients of an explosion-quake signal

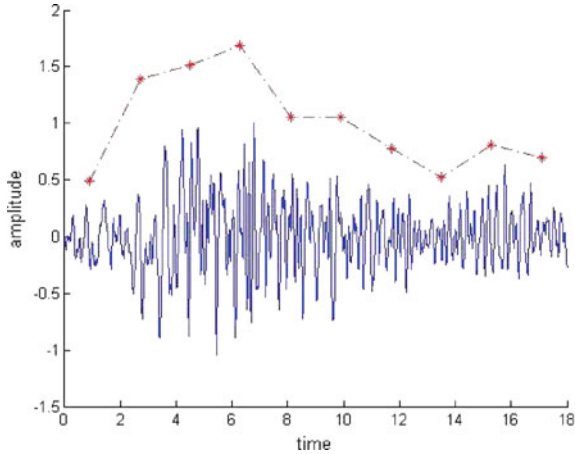


Table 2.1 The dataset distribution for the MLP training, validation and testing

	Training (50%)	Validation (20%)	Testing (30%)
Explosion-quakes (429)	214	85	130
Hybrid events (455)	227	92	136
	441	177	266

2.4 MLP Technique

For the discrimination task we adopted a Multi-Layer Perceptron (MLP) [2] network. Neural networks have proved to be effective in several applications and fields [7, 8, 13, 15, 17, 25, 29, 30] thanks to their learning ability from the experience and to be data-driven methods. Moreover, they are non-linear models and can represent complex data relationships.

In our experiments, the dataset for each class of signals was partitioned into training, validation and testing sets as shown in Table 2.1. In particular, the training set was composed of 441 input vectors (227 hybrid events and 214 explosion-quakes). The same training set was used for all the experimental conditions detailed in Table 2.2. The validation process is done in order to find the optimal number of iterations to be used in the training process.

Then, the net parameters adjustment was realized taking into account previous works [13, 17] and using a trial and error procedure. Regarding to the MLP architecture, we used a variable number of hidden nodes, a nonlinear hyperbolic-tangent function for the hidden nodes and a logistic sigmoidal activation function for the output unit. The weight optimization was carried out through two algorithms, i.e. the Quasi-Newton and the Conjugate Gradient [2]. Finally, during the training, instead of the conventional mean square error (MSE) function,

Table 2.2 The MLP performances obtained varying the number of the hidden nodes (X) and the input vector dimension expressed as the number of LPC coefficients (Y) with or without a fixed number (i.e. 10) of waveform coefficients. The best performances are in cyan color

Conjugate Gradient					
Y/X	2	4	6	8	10
6	88.90%	88.55%	88.55%	88.75%	87.75%
8	80.65%	82.70%	85.75%	86.45%	60.90%
10	89.65%	87.40%	88.90%	90.20%	84.95%
12	91.75%	88.35%	88.90%	88.70%	88.00%
14	90.05%	90.95%	90.60%	90.05%	91.00%
16	88.75%	90.00%	91.75%	90.60%	91.35%
8+10(wave)	97.00%	98.50%	97.55%	97.55%	98.70%
10+10(wave)	98.10%	98.30%	98.85%	98.85%	97.35%
12+10(wave)	96.95%	97.35%	98.90%	97.95%	98.10%
14+10(wave)	97.95%	97.90%	99.05%	97.20%	99.25%
16+10(wave)	98.30%	98.85%	99.05%	98.30%	97.00%
18+10(wave)	98.65%	97.75%	98.15%	97.55%	98.45%
20+10(wave)	98.10%	98.30%	98.90%	98.15%	97.95%

Quasi New					
Y/X	2	4	6	8	10
6	90.00%	87.75%	86.50%	88.90%	87.60%
8	72.60%	80.45%	87.00%	85.35%	70.70%
10	87.05%	87.20%	89.30%	89.30%	84.40%
12	93.05%	87.95%	88.90%	90.20%	88.00%
14	89.50%	90.75%	90.80%	89.65%	91.00%
16	89.10%	90.80%	91.90%	91.00%	91.35%
8+10(wave)	96.85%	98.65%	96.60%	97.35%	98.70%
10+10(wave)	98.50%	98.30%	98.30%	98.50%	97.90%
12+10(wave)	96.95%	97.90%	98.90%	98.60%	97.35%
14+10(wave)	97.75%	98.85%	98.90%	97.20%	99.25%
16+10(wave)	98.30%	99.20%	99.05%	98.45%	97.35%
18+10(wave)	98.15%	96.95%	97.95%	97.40%	98.10%
20+10(wave)	97.55%	98.30%	97.90%	98.15%	97.20%

we minimize the Cross-Entropy Error Function [2]. Combining logistic output units and this error function, the network response indicates the probability that a certain input belong or not to one of two classes, providing a probabilistic interpretation.

2.5 Results

In the following we illustrate the results of the MLP discrimination on the testing set by using the Conjugate Gradient and the Quasi-Newton learning algorithm respectively (Table 2.2). The performances are obtained varying the number of the

hidden nodes and the input vector dimension. In particular, we first used only the LPC coefficients, then we added a fixed number of waveform coefficients (i.e. 10). The best performances are indicated in cyan color. In the Table 2.2, X indicates the number of the hidden nodes, while Y is the number of the LPC coefficients.

2.6 Conclusions

A neural strategy is proposed in order to detect and discriminate hybrid events recorded at Stromboli volcano from the typical explosion-quakes. Hybrid signals are a particular typology of events often associated to fault failure in the volcanic edifice due to magma movement and/or pressurization [19]. Their analysis can improve the eruptive process comprehension. However, it is difficult to distinguish them from the explosion-quakes by using only a visual inspection of their seismograms. So, to accomplish this aim, first we encoded data by using their discriminating features. In particular, we applied the LPC technique [20, 23] for extracting the spectral content of both signals, and a waveform representation to obtain their temporal features. Then, we selected a Multi-Layer Perceptron [2] network to realize the discrimination task.

As visualized in Table 2.2, the best performances was obtained with an input dimension between 22 (i.e. 12 LPC coefficients + 10 waveform coefficients) and 26 (i.e. 16 LPC coefficients + 10 waveform coefficients) and with a number of hidden nodes between 4 and 6. Moreover, a sudden increase in accuracy, from 88–94% to 97–99%, was reached when the waveform features are coded together with LPC coefficients as input to the network, emphasizing the importance of temporal features for discriminating hybrid events from explosion-quakes.

The achieved results demonstrate that the proposed method, based on the MLP network, well discriminate the two classes of signals. So, it could be included in an advanced automated system for the monitoring of Stromboli and of other volcanoes in the world.

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